EVENT STUDY ANALYSIS OF CONSUMER BEHAVIOR: EVIDENCE FROM CREDIT CARD SPENDING IN KOREA

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EVENT STUDY ANALYSIS OF CONSUMER BEHAVIOR: EVIDENCE FROM CREDIT CARD SPENDING IN KOREA

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This dissertation uses proprietary credit card data to investigate the impact of several shocks on consumer's spending behaviors. The shocks studied consist of a regulatory shock initiated by the Korean government, an emotional shock from a human-made calamity, and a security shock stemming from a high-profile information security breach. Chapter 1 introduces the motivations behind this dissertation and gives a summary of each chapter.

Chapter 2 discusses the regulatory shock. In South Korea, credit card holders can subscribe to a messaging service that sends a cell phone text message whenever a credit card purchase is made. Since September 2012, Korean policymakers have required that these text messages also include information on unpaid debt balances. Comparing credit card spending by users who subscribe to this messaging service and by users who do not shows that reminders of unpaid debt balances reduce credit card spending by 1%, past due balances by 0.5%, and installment purchases by 0.5%. These findings suggest that simple reminders of unpaid debt balances can lead to more responsible spending.

Chapter 3 examines the effect of social grief on credit card spending. In April 2014, a South Korean ferry carrying 476 people, mostly secondary school students from the city of Ansan, capsized, leading to 304 deaths in a disaster that devastated the entire country. This research finds that spending decreased dramatically after the

disaster, especially among people living in Ansan. These findings suggest that social grief can reduce consumer spending.

Chapter 4 explores the effect of the high-profile information security breach on consumer credit card spending. On January 8, 2014, Korean regulators announced that the details of 104 million credit cards had been stolen, affecting nearly 20 million individuals. This research finds empirical evidence that such a massive information security breach increases the likelihood of account cancellation and reduces the use of the compromised credit card.

Chapter 5 concludes with a summary of main findings of the dissertation and suggests directions for future studies on consumer behavior.

BIOGRAPHICAL SKETCH

Young Hwa Seok was born in Busan, Republic of Korea. After completing her high school education at the Masters School in New York in 1998, Young Hwa entered Mount Holyoke College, where she earned a bachelor's in science, with a major in economics and a minor in math. After graduating from Mount Holyoke in 2001, she joined the marketing team at American International Group (AIG)-Life Insurance in Korea.

To cultivate her understanding of the financial market, Young Hwa earned her master's in business administration and law (LL.M.) at Yonsei University in Seoul, Republic of Korea, in 2005 and also passed the American Institute of Certified Public Accountants exam in 2006. In 2007, she joined the KB Research Institute of KB Kookmin Bank in Seoul, Republic of Korea, as a full-time researcher. During her four years of service at KB Kookmin Bank, Young Hwa researched a wide range of topics relating to economic crises and banking regulations.

To better equip herself as a professional researcher, Young Hwa joined Cornell University and completed her doctorate in philosophy (Ph.D.) in applied economics and management in August 2017.

To my family, for their endless love and support

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CHAPTER 1

INTRODUCTION

Credit cards provide a payment method that enables cardholders to pay merchants for goods and services without using money out of pocket. As well as convenience, credit cards offer an extra cash source for urgent financial needs and provide consumers with an easy way to track expenses. Being indebted is a long-standing source of discomfort and even embarrassment, but this attitude is challenged by the consumer culture, an economy defined by the buying and spending of consumers. Consumer culture serves as a powerful force changing social attitudes toward debt as credit card debt becomes commonplace. In the United States, for example, credit card payments reached $33.8 billion in 2015, increasing steadily at an annual rate of 8.0 percent from 2012.[1]

Social concerns, however, arise about whether credit cards encourage over-indebtedness, especially among those least able to pay. Some studies show that consumers' willingness to pay increases when using credit cards (Prelec & Loewenstein, 1998; Prelec & Simester, 2001). The widespread popularity of credit cards and growing concerns about debts emphasize the importance of understanding the role of credit cards in consumer behavior. Despite a sizeable literature on consumer behaviors, few studies use high-quality datasets to empirically investigate consumer behavior.

This dissertation, therefore, offers several case studies from a unique dataset on credit card accounts and illustrates the impact of various environmental changes on consumer behavior. This study uses a proprietary dataset from one of Korea's largest

[1] https://www.federalreserve.gov/newsevents/press/other/2016-payments-study-20161222.pdf

credit card issuers that contain a panel of thousands of individual credit card accounts. The case studies in this dissertation concern a regulatory shock caused by the Korean government, an emotional shock from a human-made calamity, and a security shock stemming from a high-profile information security breach. The case studies occur in natural settings; therefore, this dissertation provides empirical evidence to answer questions asked in real-life settings.

Chapter 2 presents a study on government attempts to use nudges to influence debt control. This chapter focuses on whether increasing awareness of consumers' unpaid debt balances reduces credit card debt. In this case, a nudge is given by text message reminders intended to encourage responsible spending behavior by consumers. In South Korea, credit card holders can sign up to receive instantaneous transaction alerts via text messages for a fee of less than $1 per month. To raise the limited self-awareness of credit card debt and to promote responsible spending behaviors, Korean policymakers in September 2012 required that the transaction alerts include information about unpaid debt balances. Before implementation of this policy, subscribers to the service (hereafter, SMS-users) received only transactional information, such as the sales total, purchase time, and vendor name. The new policy requires credit card companies to give SMS-users the option to receive free unpaid-debt alerts at the bottom of the screen showing the transaction information.

Using an account-level credit card dataset, this study examines the effect of unpaid debt reminders on credit card behavior, which includes credit card spending, past due balances, installment purchases, and the likelihood of accumulating past due balances. The behavior of SMS-users who receive unpaid debt reminders and those who do not subscribe to the service (hereafter, Non-SMS-users) is compared using two approaches: a regression model with fixed effects and difference-in-differences estimations. The regression model uses an original dataset and estimates a fixed-effect regression, and a new dataset is constructed for the difference-in-differences estimations by matching and comparing the mean differences in credit card behaviors before and after September 2012. The results from both approaches suggest that reminding consumers about unpaid debt balances influences credit-card usage behaviors. Specifically, reminders of unpaid debt balances reduce credit card spending by 1 percent, past due balances by 0.2 percent, and the likelihood of past due balances by 0.3 percent. Moreover, reminders are especially effective for cardholders who have low credit scores. The findings offer a potential foundation to develop a nudge policy.

While Chapter 2 focuses on government nudge policies, Chapter 3 presents a study on emotions and credit card spending, specifically examining the impact of the national tragedy on credit card spending. An event discussed in this chapter is the *Sewol* ferry disaster in April 2014, when a South Korean ferry carrying 476 people, mostly secondary school students from Ansan, capsized. Ultimately, 304 people died, and while the disaster devastated the entire country, it is hypothesized that: 1) the event caused especially high emotional distress in Ansan; and 2) this community distress is reflected in credit card spending, although the disaster caused little financial damage beyond the tragic loss of human life.

This chapter investigates consumer reactions to the *Sewol* disaster and possible associations between changes in credit card consumption and physical proximity to the victims or their families. Zip codes in the dataset are used to locate cardholders' residences at the sub-municipal level and categorize them by the distance to the victims' residences. Fixed-effects regressions and difference-in-differences estimations find that after the ferry disaster, residents of the neighborhood of Ansan where the most victims lived reduced spending by 4 percent more than the rest of the country. People in the greater city of Ansan disproportionately decreased spending by 1.6 percent. The observed reductions in spending are especially strong among women and those in the age 40–50 years group. These results suggest that emotional distress can significantly dampen consumer sentiment and, consequently, consumer spending. This chapter also identifies consumers who react more sensitively to public disaster based on empirical evidence. These findings can help policymakers better prepare for future disasters.

Chapter 4 studies consumer reactions to a high-profile information security breach. Today, many organizations collect and store customer data to provide more personalized services to customers. Customized approaches are especially important to increase credit card companies' ability to achieve market competence. While understanding large volumes of customer data may enable companies to improve customer engagement, little is known about the actual outcomes when companies fail to protect customer information. However, data breach incidents are increasing worldwide, and some of the worst cases compromise the private information of millions of customers.

Repeated security breaches and growing interest in the use of customer information lead to consideration of how customers react to security breaches. Chapter 4 focuses on a major security breach among Korean credit card companies in 2014 that was among the largest in the country's history and affected more than 20 million cardholders in the country of 50 million. In January 2014, Korean regulators announced that an information technology worker had stolen the details of 20 million cardholders from three Korean credit card issuers (KB Financial Group, NongHyup Financial Group and Lotte Group) and sold the data to loan marketing companies. The stolen data included personal and financial information, such as names, residential addresses, telephone numbers, social security numbers, salaries, and credit card details.

The proprietary data analyzed in this chapter come from one of three data-leaked card issuers. Although the dataset does not indicate whose information was breached, the announced number of affected users suggests that the majority of customers in the dataset were compromised. Comparing the behaviors of likely affected cardholders before and after the breach allows investigating changes in customer spending behaviors and the likelihood of account closure after major security breaches. These findings suggest that information security breaches motivate customer intention to leave compromised companies, and this trend persists for several months. Moreover, although some customers decide to stay, retaining accounts does not guarantee continued use of services because customers also reduce use of compromised credit cards after breaches.

To confirm whether these changes in behaviors are related to the breach, an additional public dataset from Financial Statistics Information System is used. A fixed-effects regression model examining the credit card usage for 20 card issuers in Korea suggests a pronounced decrease in credit card usage among the data-leaked companies during the second quarter after the breach. The findings in this chapter contribute to the knowledge of security breaches and customer reactions to major security failures by particular companies, providing useful insights to policymakers and risk managers in credit card industries.

Chapter 5 summarizes the main findings and implications for each case study. This chapter also presents suggestions for future research and directions to extend work on consumer behavior.

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CHAPTER 2

EFFECT OF UNPAID DEBT REMINDERS ON CREDIT CARD BEHAVIORS

1. Introduction

Household finances play an important role in driving economic growth (Mian & Sufi, 2009) as well as in explaining financial crises (Schularick & Taylor, 2012), so voluntary efforts undertaken by individuals to control their debt warrants attention. As is true in many other countries, the growing trend toward overuse of and defaulting on credit card debt has raised concerns in Korea involving the limited self-awareness that consumers seem to have regarding their credit card borrowing, calling for interventions to assist individuals who cannot manage their debt.

To enable banks and other card-issuing companies to warn consumers about their unpaid debt, in September 2012 Korean policymakers made it possible for credit card users to use a credit card SMS (Short Message Service) to alert them of unpaid charges for which they are responsible. Before implementing the policy, credit card companies used SMS to prevent fraudulent charges for consumers who subscribed to the service, delivering transactional information such as sales totals, times of purchases, and vendor names. Whenever SMS-users swiped their credit cards, they received SMS-generated text messages along with transactional information delivered immediately to their mobile phones. The new policy required credit card companies to give users the option of receiving unpaid debt alerts at the bottom of the screen showing the other information. While this additional service would increase the cost of providing SMS for credit card companies, it is free for users. This in effect turns a smartphone into a device capable of encouraging consumers to exercise debt control.

Unpaid debt balances consist primarily of unpaid debt principal, such as the sum of unpaid debts from cash advances and unpaid balances following minimum payments, but exclude fees and interest. Unpaid debt balances differ from payments due in that unpaid debts include debts that must be repaid in the current month and accumulated debts deferred from previous billing periods, while payments due include the sum of debts within a billing cycle and a portion of deferred debts from previous billing periods. As such, unpaid debts are typically much higher than payments due for a given billing cycle. Moreover, while payments due statements indicate specific due dates for repayments and are subject to immediate collection, unpaid debt balances reported through the SMS do not have due dates and may take several months to be fully paid off. By highlighting the full debt owed, unpaid debt reminders are designed to maximize consumer anxiety about debt and eventually to induce consumers to reconsider their purchasing habits.

Using an account-level credit card dataset, this chapter examines the effect of unpaid debt reminders on credit card user behaviors. I used credit card spending, past due balances, installment purchases, and the likelihood of accumulating past due balances as proxies for credit card user behaviors, and compared the behavior of SMS-users who receive unpaid debt reminders with the behavior of Non-SMS-users who had never subscribed to an SMS. I find that, after receiving unpaid debt reminders, SMS-users spend on average 1% less than Non-SMS-users when using their credit cards. Moreover, unpaid debt reminders have a statistically significant effect on reducing past due balances as well as on the use of installments, suggesting that a reminder reduces the tendency to procrastinate when making repayments. I also find that unpaid debt reminders are effective in reducing the likelihood of accumulating past due amounts. To confirm the reliability of my results, I estimate the mean difference-in-differences using a matched dataset. Before running the difference-in-differences estimation, I construct a new data set to control for covariates. To observe similarities in the backgrounds of SMS-users and Non-SMS-users, I average five covariates—age, credit limits, spending, the number of uses, and uncharged debt balances—and estimate a propensity score, a single matching variable, using a probit model. I find that difference-in-differences results are consistent with my results using a fixed-effects regression model.

II. Understanding the Behavior of SMS-Users

While credit card policies have aimed to manage household debt by focusing on monetary measures designed to constrain consumer spending habits, such as tightening liquidity constraints and applying high interest rates, such measures do not directly treat consumer psychology as an antecedent of debt control. The prospect of having to pay a large debt produces anxiety (Drentea, 2000; Callender & Jackson, 2005), and individuals have incentives to lessen anxiety, particularly if it damages their self-concepts (Markus & Wurf, 1987). The psychology underlying behavior associated with unpaid debt reminders is also understood in part as the result of a desire to minimize the threat posed by debt, of which consumers are continuously aware as they receive SMS text messages.

Responsiveness to information generally increases with salience (Klibanoff et al., 1998; Barber et al., 2005; Chetty et al., 2009). Salience is important in this study since reminders are less effective if the information they convey is not salient. I believe the unpaid debt reminders in this study are salient, for two reasons: 1) news about the unpaid debt reminder SMS policy appeared widely in newspapers when it became a default option for SMS-users, which makes it likely that consumers were aware of the policy; and 2) adding unpaid debt balances does not make an SMS text message complicated; information about unpaid debt balances is located at the end of a concise presentation of transactional information (shown in Figure1.1)

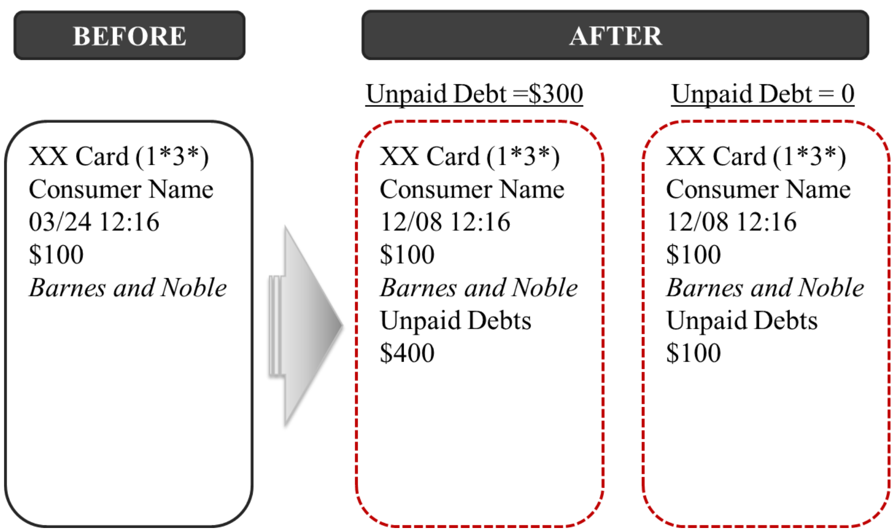

Figure 1.1: Before and After Unpaid Debt Reminders

Although I am confident about the saliency of the debt reminders involved in this study, whether all consumers pay the same level of attention to SMS text messages is doubtful. Studies in the marketing literature increasingly note the effectiveness of repetitive advertisements in affecting consumer attention, attitudes, recall, and cognitive acceptance (Hutchinson & Alba, 1991; Winter, 1973; Craig et al., 1976; Cacioppo & Petty, 1979). Personal involvement with a brand is particularly important in terms of delaying the stage at which the effectiveness of repetition diminishes, or a wearout effect occurs (Campbell & Keller, 2003; Shiv et al., 1997). Although the unpaid debt reminders under this study are not advertisements per se, I believe that consumer responses to repetitive SMS messages should be similar to their reactions to repetitive advertising. In this regard, I capture my expectations in the following hypotheses:

H0: Credit card spending, late payments, installment purchases, and the likelihood of accumulating past due payments will not change for SMS-users after receiving unpaid debt reminders.

H1: Credit card spending, late payments, installment purchases, and the likelihood of accumulating past due payments will change for SMS-users after receiving unpaid debt reminders.

This chapter suggests that reminders enhance cardholder welfare. Indeed, reminders are found to be effective in various domains, such as preventing bad habits (Koritzky & Yechiam, 2011), keeping appointments (Friman et al., 1985; Watanabe-Rose & Sturmey, 2008), increasing daily activities (Schwerdtfeger et al., 2012), and driving people to vote (Dale & Strauss, 2009). This study also contributes to the extant literature that concentrates on the effects of reminders on changing individual behavior. The use of reminders, however, has been of little interest in consumer finance until recently, and to the best of my knowledge, no study has used empirical data to observe the effects of reminders on credit card behaviors. The rare exceptions consist mostly of studies in which the effects of reminders are examined in experimental settings. For example, to compare the effect of a range of incentives on loan repayments in microfinance institutions, Cadena and Schoar (2011) conducted a field experiment wherein borrowers chose one of three treatments—cash rewards, interest rate reduction, or a monthly text message that remind them of payment due dates—and found that monthly reminders are as effective as 25 percent reductions in interest rates in terms of improving payment discipline. Moreover, Karlan et al. (2010) conducted a field experiment to investigate the effects of reminders on saving. To observe whether there exist distinctive outcomes that vary with message content, they sent two types of reminders, one with additional comments about future expenditure opportunities and the other without such comments, and found that people who receive the former message tend to save more than those receiving the latter message. Kast et al. (2014) also conducted a field experiment with micro-entrepreneurs to examine the effect of commitment devices on savings and used peer and feedback messages as treatments.

The rest of the chapter proceeds as follows. In Section III, I describe the data sources and regression variables. Section IV estimates the models and presents the results. SectionV tests for robustness, and Section VI concludes.

III. Data Description

3.1 Sources

I obtained the data used in this chapter mainly from a large credit card company in Korea. My data include 13 million year-month observations provided by 0.7 million cardholders whose last name is “Kim.” “Kim” is the most common surname in Korea, which suggests that the behavior of the cardholders in this sample represents the behavior of Korean cardholders generally. Each account represents a single monthly statement for all cards issued by the company, as cardholders may own multiple credit cards from the same company. The sample period runs from January 2012 through June 2013, which includes September 2012, when unpaid debt reminders were first implemented. To exclude inactive credit card holders, I consider only cardholders who spend more than ten dollars in each month of the study period. I also exclude cardholders who subscribed to SMS after September 2012. The age range of individuals in the sample runs from 18 to 80 years. The data form an unbalanced panel consisting of non-sensitive and non-traceable information about cardholders such as gender, age, credit limits, card spending, and past due balances.

3.2. Regression Variables

3.2.1. Credit Card Behavior Measures

To measure cardholder behaviors, I use the following dependent variables: *ln(Spending)*, *ln(PastDue)*, *Install_Use_Ratio* and *dPastDue. ln(Spending)* represents the log of monthly spending plus one and consists of all transactions made with credit cards, including cash advances. *ln(PastDue)* represents the log of monthly past due balances plus one and consists of unpaid debt balances from previously charged debt including unpaid debt from cash advances, but does not include late fees or interest. *Install_Use_Ratio* represents the ratio of installment purchases to total credit card transactions and is used to understand the consumer habit of procrastination. It is calculated by dividing the number of monthly installment purchases by the number of monthly credit card transactions. To count installment purchases, I add the number of uses of both revolving and installment credit. In Korea, cardholders are typically given two options for delaying payments, revolving credit and installment credit. While the former repayment method is a commitment made after consumption without promising a specific date for full redemption and the amount can vary from a minimum payment to a specific portion of the debt, the latter is a decision made before a purchase based on a consumer's judgment regarding her financial condition and the amount of each monthly payment is the same over the period to which the consumer commits. Unlike in many other countries, where installment credit applies only to costly products such as cars and furniture, installment credit is quite prevalent in Korea to pay credit card debt ranging from $50 purchases to purchases of several thousand dollars, as long as credit allows. Lastly, *dPastDue*, used in a logistic regression, is a binary variable that equals one if a cardholder defaults on payments and zero otherwise.

3.2.2. SMS-users vs. Non-SMS-users

I segment cardholders into SMS-users, defined as cardholders who subscribe to SMS, and Non-SMS-users, defined as those who do not subscribe. SMS-users are able to pay less than one dollar per month for SMS and receive prompt text messages regarding their credit card transactions. Since 2012, these users have also received additional information in the form of unpaid debt reminders. I therefore classify a cardholder as an *SMS-user* if she has subscribed to the SMS and continues to receive SMS messages through the remainder of the study period, and as a *Non-SMS-user* if she does not subscribe to the SMS. Since Non-SMS-users never subscribe to the SMS, they experience no SMS-related "shock." The variable *dSMS* equals one for being an SMS-user and zero otherwise. The treatment is receiving an unpaid debt reminder, and the period is segmented by the application of the treatment. Therefore, pre-treatment is defined as the period before September 2012 and after-treatment is the period after September 2012.

3.2.3. Other Regression Variables

Additionally, I employ the following explanatory variables as controls: *ln(Credit Limit), ln(Usage), lag_ln(Uncharged)* and *dSMS_Post*. *ln(Credit Limit)* is the log of the credit limit plus one. A credit limit is assessed by the credit card company using internal and external sources to evaluate cardholders' credit-worthiness. *ln(Usage)* is the log of monthly usage of credit cards and *lag_ln(Uncharged)* is the log of the previous month's uncharged debt balance. Assuming that a high level of unsettled debts can affect consumption, I use the previous month's uncharged debt as a proxy for outstanding debt to distinguish the effects of reminders from the effects of debt outstanding. Uncharged debt is based on all transactions including revolving credit and debt accrued after a billing cycle; it does not include fees or past due balances. Although some portion of the outstanding debt is excluded, uncharged debt in general comprises a major portion of outstanding debt, which is likely to make it an effective measure of outstanding debt in determining credit behavior. Lastly, *dSMS_Post* is an interaction variable that equals one for SMS-users in after-treatment periods and zero otherwise. I also include time and individual dummies to control for time trends and individual-specific characteristics.

IV. Effects of Unpaid Debt Reminders

In this section, I examine the effects of unpaid debt reminders using two approaches: a regression model with fixed effects and difference-in-differences estimations. For the regression model, I use an original dataset and estimate a fixed-effect regression, and for the difference-in-differences estimations, I construct a new dataset using matching and compare the mean differences in credit card behaviors before and after September 2012.

4.1. Fixed-Effects Regressions

4.1.1. Descriptive Statistics

In Table 1.1, I present the descriptive statistics for cardholders in the sample. Each column in Table 1 shows the mean and standard deviation for the entire sample population, Non-SMS-users, and SMS-users, respectively. *Fraction Male* indicates the ratio of male cardholders to female cardholders and *Age* represents the average age of cardholders within a range of 18 to 80 years. *Holding Months* represents how many months a consumer holds a credit card and *Credit Limit($)* is the average dollar amount of the credit limit that is assessed by the credit card company based on cardholders' credibility. *Monthly Usage* is the average usage of credit cards per month and *Monthly Install_Use_Ratio* is the installment ratio calculated as the total number of installment purchases divided by the total number of credit card transactions.

Monthly Spending ($) is the average of monthly spending that covers cash advances and all transactions made by credit cards including revolving and installment credit purchases. *Monthly Uncharged Debt ($)* is the average monthly uncharged debt balance, which includes uncharged debts from all credit card transactions including revolving and installment credits but not including past due balances or fees. *Monthly Revolving ($)>0* is a revolving debt balance that is greater than zero. *Monthly Install Debt($) >0* is an average installment debt balance that is greater than zero, and *Monthly Past Due($)>0* is the past due payment that is greater than zero.

Table 1.1: Descriptive Statistics

	All		***Non-SMS-user***		***SMS-user***	
Number of Observation	13,186,702		1,416,252		11,770,450	
Number of Individuals	745,020		79,753		665,267	
Fraction of Male	0.52		0.54		0.52	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Age	44	11	53	11	43	10
Holding Months	17.7	1.31	17.8	1.23	17.7	1.33
Credit Limit ($)	6,061	4,834	6,049	4,972	6,062	4,817
Monthly Usage	18	16	12	12	18	17
Monthly Install_Use_Ratio	0.51	0.46	0.38	0.45	0.52	0.46
Monthly Spending ($)	975	1,374	847	1,299	990	1,382
Monthly Uncharged Debts ($)	1453	2,083	1283	2,094	1474	2,081
Monthly Revolving($)>0	753	1,057	580	864	767	1,069
Monthly Install Debt($) >0	507	820	466	736	512	828
Monthly Past Dues ($) >0	459	810	481	932	456	790

Comparing the descriptive statistics for Non-SMS-users and SMS-users, I find that 89 percent of cardholders in the sample subscribed to SMS, as indicated by *Number of Individuals* (0.6 million for SMS-users vs. 0.08 million for Non-SMS-users). SMS-users in the sample are on average younger than Non-SMS-users (43 years of age for SMS-user vs. 53 years of age for Non-SMS-users), which makes sense since younger people are in general more familiar with using cell phones and conducting financial activities over the Internet. There are no significant differences between SMS-users and Non-SMS-users in terms of *Holding Months* or *Credit Limit*—members of both groups have been using credit cards for more than a year with credit limits above $6,000. SMS-users, however, tend to swipe credit cards more often (18 times per month for SMS-users vs. 12 times per month for Non-SMS-users), allot more of their transactions to installment purchases (52% for SMS-users vs. 38% for Non-SMS-users), and spend more than Non-SMS-users ($990 for SMS-users vs. $847 for Non-SMS-users). Moreover, SMS-users tend to carry more uncharged debt ($1,474 for SMS-users vs. $1,283 for Non-SMS-users), revolving balances ($767 for SMS-users vs. $580 for Non-SMS-users), and installment debt ($512 for SMS-users vs. $466 for Non-SMS-users). Regarding past due balances greater than zero, however, Non-SMS-users tend to carry more than SMS-users ($456 for SMS-users vs. $481 for Non-SMS-users).

4.1.2. Fixed-Effects Regressions

To estimate the effect of unpaid debt reminders, I use fixed-effect regressions. Standard errors are clustered by "mean credit card usage." I calculated "mean credit card usage" by averaging a cardholder's monthly credit card usage for the total study period ("number of swipes") and save an integer of the average. The regression model takes the following form:

$$Y_{it} = \alpha_i + \beta_{1-3}X_{it} + \gamma_1 dSMS_i\_Post_t + \varepsilon_{it}$$

The dependent variable Y_{it} measures the credit behavior of individual *i* at time *t*, and consists of four variables: *ln(Spending)*, *ln(PastDue)*, *Install_Use_Ratio*, and *dPastDue*. I use *ln(Spending)*, *ln(PastDue)*, and *Install_Use_Ratio* for the fixed-effects regression, and *dPastDue* for the logistic regression with fixed effects. *ln(Spending)* and *ln(PastDue)* are calculated as the log of monthly card spending plus one and the log of monthly past due balances plus one, respectively. *Install_Use_Ratio* is calculated by dividing the sum of installment transactions by the total number of credit card transactions. *dPastDue* is a binary variable that equals one if the past due balance is greater than zero and zero otherwise. The estimated coefficient β_{1-3} indicates the effect of changes in credit limits *ln(Credit Limit)*, the previous month's uncharged debt *lag_ln(Uncharged)*, and the number of credit card transactions *ln(Usage)*. I was especially interested in the coefficient γ_1, which measures the effect of unpaid debt reminders on SMS-user behavior. I also control for seasonality and time trends with time dummies,$Time_{Jan.2012}$ through $Time_{June2013}$.

4.1.3. Results of Fixed-Effects Regressions

Table 1.2 presents the results of fixed-effects regressions with *t*-statistics in parentheses. Results shown in column (1) show that credit card spending for SMS-users decreases after receiving unpaid debt reminders, as denoted by a statistically significant coefficient of -0.010 (*t*-statistic = -5.04) in *dSMS_Post*. That is, receiving a reminder of unpaid debt balances corresponds to an expected decrease in spending of approximately 1 percent for SMS-users. Given that the average spending for SMS-users equals $990, this is equivalent to an approximately $120 decrease in yearly credit card spending per individual.

Table 1.2: Results from Fixed-Effects Regressions

	ln(Spending)	*ln(Past Due)*	*Install_Use_Ratio*	*dPastDue*	
	(1)	(2)	(3)	(4)	(5)
ln(Credit Limit)	0.161***	-0.022***	0.017***	0.006	0.000
	(43.36)	(-8.02)	(15.29)	(0.53)	(0.51)
ln(Usage)	0.985***	-0.005***	-0.021***	-0.042***	-0.003***
	(44.46)	(-5.42)	(-11.10)	(-4.81)	(-4.00)
lag_ln(Uncharged)	0.015***	0.014***	0.004***	0.167***	0.012***
	(15.73)	(23.32)	(11.33)	(37.88)	(10.03)
dSMS_Post	**-0.010*** **	**-0.002** **	**-0.005*** **	**-0.036* **	**-0.003* **
	(-5.04)	**(-2.03)**	**(-5.90)**	**(-1.79)**	**(-1.76)**
ln(Spending)		-0.013***	0.030***	-0.246***	-0.018***
		(-15.14)	(16.88)	(-43.44)	(-11.95)
Individual FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
r2	0.407	0.002	0.022		
N	12.2mil	12.2mil	12.2mil	879000	879000

T-statistics are reported in parentheses with a statistical significance for p < 0.1, p < 0.05 and p <0.01 denoted by *, **, and ***, respectively.

Column (2) shows that past due balances decrease with unpaid debt reminders, as shown by a statistically significant coefficient of -0.002 (*t*-statistic = -2.03) in *dSMS_Post*, which has the economic significance of a 0.2 percent decrease in past due balances. Moreover, as denoted by a statistically significant coefficient of -0.005 (*t*-statistic = -5.90) in *dSMS_Post*, as shown in column (3), SMS-users tend to make proportionately fewer installment purchases, by 0.5 percent, after receiving unpaid debt reminders. I also present the results of the logistic regression in column (4) and the marginal effects in column (5), where I report the finding that unpaid debt reminders have a significant effect on reducing the likelihood of accumulating past due balances. Specifically, after receiving unpaid debt reminders, the likelihood of accumulating past due balances decreases by 0.3 percent (*t*-statistic = -1.76) at the 10 percent significance level.

4.2. Difference-in–Differences Estimation

4.2.1. Matching Method

To confirm the reliability of my results, I estimate the mean difference-in differences using matched datasets. Before running the difference-in-differences estimation, I constructed a new dataset to control for covariates. To observe background similarities between SMS-users and Non-SMS-users, I averaged five covariates—age, credit limits, spending, number of transactions, and uncharged debt balances. Based on the averaged covariates, I estimated a propensity score, a single matching variable, using a probit model. After cardholders are assigned a propensity score, I matched SMS-users with Non-SMS-users who have the same propensity scores to five decimal places. The matching order is randomized and pairing groups are used more than once as a match.

Table 1.3 presents the descriptive statistics after matching. As in Table 1.1, the columns in Table 1.3 show the mean and standard deviations for the entire sample population, Non-SMS-users, and SMS-users, respectively. After matching, the total number of individuals in the sample increases to one million, as half a million individuals each are assigned to the SMS-user and Non-SMS-user groups. Moreover, the means of the matched variables—age, credit limits, spending, number of transactions, and uncharged debt balances for SMS-users and Non-SMS-users—all became similar after matching compared with the means shown in the descriptive statistics in Table 1.1.

Table 1.3: Descriptive Statistics after Matching

	All		***Non-SMS-user***		***SMS-user***	
Number of Observation	19,289,060		9,640,165		9,648,895	
Number of Individuals	1,089,314		544,657		544,657	
Fraction of Male	0.52		0.53		0.52	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Age	44	10	44	10	44	10
Holding Months	18	1	18	1	18	1
Credit Limit ($)	6,181	4,935	6,247	5,014	6,115	4,855
Monthly Usage	17	16	18	17	16	14
Monthly Install_Use_Ratio	0.47	0	0.42	0	0.52	0
Monthly Spending ($)	984	1,338	1,008	1,340	959	1,334
Monthly Uncharged Debts ($)	1,460	2,104	1,471	2,127	1,449	2,080
Monthly Revolving($)>0	735	1,000	743	964	729	1,026
Monthly Install Debt($) >0	498	778	486	720	510	831
Monthly Past Dues ($) >0	484	844	504	866	457	812

The average age becomes 44 for both SMS-users and Non-SMS-users after matching. Moreover, *Holding Months* remains at 18 and *Credit Limits($)* stays above $6,000 for both groups. Non-SMS-users in the matched sample tend, however, to swipe credit cards more often (16 transactions for SMS-users vs. 18 for Non-SMS-users), spend more money ($959 for SMS-users vs. $1,008 for Non-SMS-users), and carry higher uncharged debt balances ($1,449 for SMS-users vs. $1,471 for Non-SMS-users). Nonetheless, SMS-users in the matched sample continue to make proportionately more installment purchases (52% for SMS-users vs. 42% for Non-

SMS-users) and carry higher installment debt ($510 for SMS-users vs. $486 for Non-SMS-users). Also, Non-SMS-users make more revolving credit transactions ($729 for SMS-users vs. $743 for Non-SMS-users) and carry higher past due balances ($457 for SMS-users vs. $504 for Non-SMS-users).

4.2.2. Difference-in–Differences Estimations

Using a matched dataset, I estimated difference-in-differences by taking the mean of credit card behaviors before and after the treatment. Let $\bar{Y}_t$ be the mean of credit card behaviors and *t* be periods that equal 0 for the pre-treatment period and 1 for the post-treatment period. Difference-in-differences takes the following form:

$$DD = [(\overline{Y_1}|SMS\_user) - (\overline{Y_0}|SMS\_user)] \\ - [(\overline{Y_1}|Non\_SMS\_user) - (\overline{Y_0}|Non\_SMS\_user)]$$

In Table 1.4, I present the average of credit behaviors in period *t* in columns (i) and (ii) and the differences-in-differences estimations in column (iii). Each of Panels A, B and C shows average levels and changes in *ln(Spending)*, *ln(PastDue)*, and *Install_Use_Ratio*, respectively. For *ln(Spending)* in Panel A, I averaged the non-missing values of *ln(Spending)* by *t* and *dSMS*, for SMS-users and Non-SMS-users, and subtracted the results shown in column (i) from the results shown in column (ii) to estimate difference-in-differences. Similarly, for *ln(PastDue)* in Panel B, I averaged *ln(PastDue)* among defaulters by *t* and *dSMS*, and subtracted the results shown in column (i) from the results shown in column (ii) to estimate difference-in-differences. To calculate *Install_Use_Ratio* in *Panel C*, I divided the sum of installment purchases by the total number of credit card transactions in each period. After calculating the monthly ratio of installment purchases to total transactions, I averaged the total again by t and *dSMS*, and then subtracted the results shown in column (i) from the results shown in column (ii) to estimate difference-in-differences.

Table 1.4: Difference-in-Differences Estimations

	Before Treat (i)	After Treat (ii)	Difference (ii)-(i)
Panel A: Average ln(Spending)			
SMS-User	13.202	13.174	-0.028***
	[0.001]	[0.001]	[0.001]
Non-SMS-User	13.197	13.175	-0.022***
	[0.001]	[0.001]	[0.001]
Difference	0.005***	-0.001***	**-0.006*** **
	[0.001]	[0.001]	**[0.001]**
Panel B: Average ln(Past Due) | Defaulters			
SMS-User	0.610	0.689	0.079***
	[0.003]	[0.003]	[0.004]
Non-SMS-User	0.656	0.738	0.082***
	[0.003]	[0.003]	[0.004]
Difference	-0.05***	-0.05***	**-0.003**
	[0.004]	[0.004]	**[0.006]**
Panel C: Average (Install_Use_Ratio)			
SMS-User	0.525	0.523	-0.002***
	[0.000]	[0.000]	[0.000]
Non-SMS-User	0.421	0.428	0.007***
	[0.000]	[0.000]	[0.000]
Difference	0.104***	0.095***	**-0.009*** **
	[0.000]	[0.000]	**[0.000]**

Standard errors are shown in square brackets.

Table 1.4 summarizes the results of difference-in-differences estimations. I find that my results are consistent with the results obtained from the regression model, as shown in Table 1.2. Specifically, Panel A shows that, after receiving unpaid debt reminders, average spending by SMS-users decreases by almost 1% relative to that of

Non-SMS-users, which in terms of economic significance equals the change in spending found in the regression model. Moreover, the relative decrease in changes of *ln(Past Due)* shown in column (iii) of Panel B and the relative decrease in changes of *Install_Use_Ratio* shown in a column (iii) of Panel C imply that unpaid debt reminders are helpful in reducing past due balances for those in danger of default as well as in weakening the tendency to delay payments.

V. Robustness Tests

In this section, I report the results of robustness tests I conducted to ensure that my results are not sensitive to alternative specifications. I use alternative periods, gender, credit score, and age, and examine fixed-effects regressions using robust standard errors adjusted for clustering by mean use of credit cards. In Appendix 1, I present the results of the robustness test. Results in Tables 1A and 1B show whether the results are consistent with those from using alternative periods. Thus I tested for the period running from July 2012 through December 2012 and also for the period running from April 2012 through March 2013. In Table 1A, the results for the dependent variable *ln(Spending)* are shown in the first column, the results for *ln(PastDue)* are shown in the second column, and the results for *Install_Use_Ratio* are shown in the third column. The results shown in Table 1A show that the degrees of the coefficients become larger as more time passes, suggesting that it takes some time until unpaid debt reminders take effect in changing credit behaviors. Table 1B exhibits the results from the logistic regression, and I find no significant effect of reminders on the likelihood of accumulating past due balances within a short time interval. As shown in Tables 1C and 1D, I tested whether the results are differentiated by gender by segmenting cardholders by gender. Table 1C shows that male cardholders are more heavily swayed by unpaid debt reminders than females in terms of spending. That is, after being reminded about unpaid debt balances, men in my sample cut 1.3 percent of their spending whereas women on average reduced their spending by 0.7 percent. On the other hand, unpaid debt reminders enhance female cardholder welfare in terms of reducing past due balances and installment purchases. Moreover, as shown in Table 1D, an unpaid debt reminder is effective only for females in terms of reducing the likelihood of accumulating past due balances, whereas it has no significant effect on male cardholders.

As shown in Tables 1E and 1F, I tested whether the results are differentiated by credit score by grouping cardholders by credit score. Table 1E shows that an unpaid debt reminder helps in reducing spending by cardholders whose credit scores fall in the upper 10 percent by 1.7 percent. The second column in Table 1E also shows that it helps to reduce past due balances, by 1 percent, for cardholders whose credit scores fall in the lower 10 percent. Lastly, I compared the credit card behaviors of cardholders across generations and show the results in Tables 1G and 1H. For this test, I averaged the age of cardholders and into a 20s–30s age group, a 40s–50s age group, and a 60 or above age group. I found that cardholders in the 40s–50s age group are most heavily influenced by unpaid debt reminders in terms of reducing spending and delaying payments. There were, however, no significant effects on the likelihood of accumulating past due balances when the ages are segmented by generation.

VI. Conclusion

In this chapter, I examined the effect of a policy of sending unpaid debt reminders via SMS, which was designed to minimize the risk of overusing credit cards. Using fixed-effects regressions and difference-in-differences estimation, I found that a simple text message that highlights unpaid debt balances enhances the welfare of cardholders. To be precise, after being reminded of their unpaid debt balances, cardholders in my sample reduced credit card spending, incurred lower past due balances, and were less likely to delay payments. Although it takes some time until unpaid debt reminders take effect and change credit card behaviors, such reminders seem to motivate cardholders to exercise debt control, especially among females and cardholders in the 40s–50s age group. I provide no theory explaining these changes in cardholder behaviors, but unpaid debt reminders seem to deepen or intensify cardholder anxiety regarding excessive debt and therefore provide psychological pressure to avoid future repayments, which subsequently generates changes in credit card behaviors.

The results reported in this study are, however, limited to active cardholders; inactive cardholders were excluded from the sample population. Determining whether consumers are active credit card users is based on the number of transactions and, to a certain extent, the ability to remember unpaid debt balances before making the next purchase, as reminders are sent to consumers after they swipe their credit cards. Although cardholders in my sample generate a relatively high level of repetition, repetition can be more widespread as individuals use other methods of payment such as cash. If individuals use credit cards only occasionally, the time intervals between previous and following purchases are extended. In such cases, the effects of reminders can be counterintuitive, as the probability that limited memory hampers the effectiveness of the reminders increases. Further research should examine the behaviors of cardholders with other relevant characteristics. Moreover, policymakers should consider cardholder characteristics in designing reminders.

APPENDIX 1:

ADDITIONAL INFORMATION AND ESTIMATES

Table 1A: Regression for Fixed-Effects Model by Month

	Y=ln(Spending)		***Y=ln(PastDue)***		***Y=Install_Use_Ratio***	
	3 month	6 month	3 month	6 month	3 month	6 month
ln(Credit Limit)	0.178***	0.161***	-0.028***	0.006*	0.009***	0.014***
	(34.45)	(44.17)	(-4.09)	(1.82)	(10.15)	(14.17)
ln(Usage)	1.011***	0.995***	-0.002*	-0.003***	-0.021***	-0.021***
	(41.35)	(42.87)	(-1.77)	(-3.70)	(-11.55)	(-11.03)
lag_ln(Uncharged)	-0.088***	-0.014***	0.010***	0.011***	0.000	0.002***
	(-60.21)	(-16.81)	(18.87)	(24.79)	(1.46)	(8.33)
dSMS_Post	**-0.006*****	**-0.007*****	**-0.000**	**-0.001**	**-0.005*****	**-0.006*****
	(-2.93)	**(-3.66)**	**(-0.09)**	**(-1.06)**	**(-11.46)**	**(-7.25)**
ln(Spending)			-0.013***	-0.012***	0.033***	0.032***
			(-15.20)	(-14.82)	(18.64)	(17.32)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.381	0.393	0.001	0.001	0.038	0.027
N	4.4mil	8.7mil	4.4mil	8.7mil	4.4mil	8.7mil

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

Table 1B: Logistic Regression and Marginal Effect by Month

	Y=dPastDue			
	3 month		6 month	
	logit	*dydx*	*logit*	*dydx*
ln(Credit Limit)	0.015	0.001	0.181***	0.035***
	(0.49)	(0.45)	(8.68)	(5.42)
ln(Usage)	0.034*	0.003*	-0.014	-0.003
	(1.93)	-1.94	(-1.29)	(-1.25)
lag_ln(Uncharged)	0.134***	0.011***	0.148***	0.029***
	(14.33)	(4.15)	(26.07)	(11.22)
dSMS_Post	**-0.042**	**-0.003**	-0.022	-0.004
	(-1.20)	**(-1.16)**	(-0.91)	(-0.90)
ln(Spending)	-0.270***	-0.022***	-0.248***	-0.048***
	(-23.82)	(-4.94)	(-34.37)	(-14.25)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	0.2mil	0.2mil	0.5mil	0.5mil

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

Table 1C: Regression for Fixed-Effects Model by Gender

	Y=ln(Spending)		***Y=ln(PastDue)***		***Y=Install_Use_Ratio***	
	Male	Female	Male	Female	Male	Female
ln(Credit Limit)	0.156***	0.167***	-0.026***	-0.019***	0.021***	0.014***
	(38.24)	(38.20)	(-6.05)	(-4.96)	(14.26)	(12.38)
ln(Usage)	1.002***	0.967***	-0.007***	-0.003**	-0.015***	-0.026***
	(45.04)	(43.39)	(-7.28)	(-2.57)	(-7.80)	(-14.88)
lag_ln(Uncharged)	0.018***	0.010***	0.013***	0.014***	0.004***	0.004***
	(19.00)	(9.26)	(20.65)	(24.31)	(11.56)	(10.49)
dSMS_Post	**-0.013*** **	**-0.007*** **	**-0.000**	**-0.003** **	**-0.005*** **	**-0.006*** **
	(-5.66)	**(-3.12)**	**(-0.34)**	**(-2.23)**	**(-5.18)**	**(-5.41)**
ln(Spending)			-0.011***	-0.015***	0.025***	0.036***
			(-12.54)	(-15.07)	(15.18)	(18.81)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.418	0.395	0.002	0.002	0.019	0.027
N	6.4mil	5.8mil	6.4mil	5.8mil	6.4mil	5.8mil

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

Table 1D: Logistic Regression and Marginal Effect by Gender

	Y=dPastDue			
	Male		Female	
	logit	*dydx*	*logit*	*dydx*
ln(Credit Limit)	-0.006	0.000	0.022	0.002
	(-0.34)	(-0.35)	(1.29)	(1.13)
ln(Usage)	-0.081***	-0.006***	-0.011	-0.001
	(-6.11)	(-4.19)	(-0.97)	(-0.93)
lag_ln(Uncharged)	0.194***	0.015***	0.145***	0.011***
	(29.25)	(7.05)	(24.56)	(7.16)
dSMS_Post	**0.003**	**0.000**	**-0.066****	**-0.005****
	(0.09)	**(0.09)**	**(-2.39)**	**(-2.28)**
ln(Spending)	-0.244***	-0.019***	-0.247***	-0.019***
	(-28.18)	(-8.43)	(-32.95)	(-8.55)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	0.4mil	0.4mil	0.5mil	0.5mil

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 1E: Regression for Fixed-Effects Model by Credit Score

	Y=ln(Spending)		***Y=ln(PastDue)***		***Y=Install_Use_Ratio***	
	Percentile		Percentile		Percentile	
	Lower 10	Upper 10	Lower 10	Upper 10	Lower 10	Upper 10
ln(Credit Limit)	0.198***	0.134***	0.045***	-0.073***	0.012***	-0.000
	(14.69)	(10.68)	(5.16)	(-3.23)	(8.14)	(-0.00)
ln(Usage)	0.941***	1.002***	-0.016***	0.001	-0.052***	-0.012***
	(38.86)	(50.41)	(-5.52)	(0.56)	(-18.12)	(-11.61)
lag_ln(Uncharged)	-0.008**	0.045***	0.024***	0.008***	0.003***	0.003***
	(-2.29)	(27.74)	(15.51)	(12.24)	(7.68)	(7.59)
dSMS_Post	**-0.010****	**-0.017*****	**-0.010****	**-0.006****	**-0.005*****	**-0.007*****
	(-2.48)	**(-3.56)**	**(-2.19)**	**(-2.12)**	**(-3.67)**	**(-7.20)**
ln(Spending)			-0.044***	-0.008***	0.056***	0.017***
			(-6.37)	(-11.55)	(24.00)	(22.09)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.465	0.328	0.004	0.002	0.043	0.014
N	1.2mil	1.3mil	1.2mil	1.3mil	1.2mil	1.3mil

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 1F: Logistic Regression and Marginal Effect by Credit Score

	Y=dPastDue Percentile			
	Lower10		Upper10	
	logit	*dydx*	*logit*	*dydx*
ln(Credit Limit)	0.295***	0.023***	-0.097	-0.008***
	(10.05)	(3.71)	(-1.54)	(-3.17)
ln(Usage)	-0.095***	-0.007***	-0.005	-0.000
	(-5.22)	(-3.25)	(-0.13)	(-0.13)
lag_ln(Uncharged)	0.104***	0.008***	0.260***	0.023*
	(11.59)	(4.69)	(11.83)	(1.95)
dSMS_Post	**-0.101****	**-0.008****	**-0.042**	**-0.004**
	(-2.42)	**(-2.22)**	**(-0.50)**	**(-0.49)**
ln(Spending)	-0.360***	-0.028***	-0.242***	-0.021**
	(-27.79)	(-5.87)	(-10.97)	(-2.14)
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	0.2 mil	0.2 mil	40,924	40,924

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

Table 1G: Regression for Fixed-Effects Model by Age

	Y= ln(Spending)			*Y=ln(PastDue)*		
	20-30s	40-50s	60s≤	20-30s	40-50s	60s≤
ln(Credit Limit)	0.169***	0.156***	0.149***	-0.020***	-0.025***	-0.015*
	(52.20)	(37.01)	(12.76)	(-4.55)	(-5.55)	(-1.70)
ln(Usage)	0.926***	1.020***	1.116***	-0.005***	-0.003***	-0.003**
	(61.29)	(42.26)	(32.70)	(-5.08)	(-2.77)	(-2.22)
lag_ln(Uncharged)	0.014***	0.018***	0.004***	0.016***	0.013***	0.008***
	(11.54)	(14.05)	(3.33)	(26.55)	(27.20)	(10.70)
dSMS_Post	**-0.002**	**-0.017*** **	**-0.014*** **	**-0.002**	**-0.002**	**-0.000**
	(-0.39)	**(-8.15)**	**(-4.29)**	**(-0.65)**	**(-1.34)**	**(-0.24)**
ln(Spending)				-0.018***	-0.011***	-0.007***
				(-17.44)	(-16.10)	(-7.92)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
r2	0.439	0.392	0.381	0.002	0.002	0.002
N	4.8mil	6.3mil	1.2mil	4.8mil	6.3mil	1.2mil

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

	Y=Install_Use_Ratio		
	20-30s	40-50s	60s≤
ln(Credit Limit)	0.022***	0.013***	0.004**
	(14.90)	(11.71)	(2.58)
ln(Usage)	-0.020***	-0.018***	-0.040***
	(-12.56)	(-9.38)	(-18.69)
lag_ln(Uncharged)	0.007***	0.002***	-0.000
	(17.21)	(11.88)	(-0.85)
dSMS_Post	**-0.004*** **	**-0.007*** **	**0.001**
	(-2.68)	**(-6.79)**	**(0.80)**
ln(Spending)	0.029***	0.029***	0.042***
	(18.41)	(16.07)	(19.25)
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
r2	0.018	0.023	0.052
N	4.8mil	6.3mil	1.2mil

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

Table 1H: Logistic Regression and Marginal Effect by Age

	Y=dPastDue					
	20-30s		40-50s		60s≤	
	logit	*dydx*	*logit*	*dydx*	*logit*	*dydx*
ln(Credit Limit)	0.031*	0.001	-0.012	-0.001	-0.024	-0.003
	(1.84)	(1.52)	(-0.67)	(-0.71)	(-0.38)	(-0.43)
ln(Usage)	-0.025**	-0.001*	-0.035***	-0.004**	-0.085**	-0.009
	(-2.07)	(-1.83)	(-2.70)	(-2.40)	(-2.24)	(-1.55)
lag_ln(Uncharged)	0.136***	0.006***	0.196***	0.022***	0.193***	0.021**
	(21.16)	(6.40)	(30.18)	(7.64)	(11.12)	(2.44)
dSMS_Post	**-0.005**	**-0.000**	**-0.004**	**-0.000**	**0.049**	**0.005**
	(-0.10)	**(-0.10)**	**(-0.16)**	**(-0.16)**	**(0.87)**	**(0.83)**
ln(Spending)	-0.297***	-0.012***	-0.213***	-0.024***	-0.190***	-0.021***
	(-34.25)	(-7.79)	(-26.52)	(-9.04)	(-8.80)	(-2.75)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	0.4mil	0.4mil	0.4mil	0.4mil	0.1mil	0.1mil

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

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CHAPTER 3

SENSE OF COMMUNITY AND CREDIT CARD SPENDING: EVIDENCE FROM THE *SEWOL* FERRY DISASTER

Do not forsake your friend and your father's friend, and do not go to your brother's house in the day of your calamity. Better is a neighbor who is near than a brother who is far away.

(Proverbs 27:10)

I. Introduction

This chapter utilizes empirical observations on household credit-card spending to examine the effect of neighborhood affiliation on credit-card consumption in the aftermath of a tragic event. In an era in which anyone can encounter unexpected tragedies due to widespread terrorist attacks or natural disasters, costing precious human lives and taking financial tolls, the aftermaths of such incidents include collective mourning and concerns for those who experience the deaths of family members. Certainly, the painful transition and trauma after a tragic event are exceptionally harsh on victims and their families.

In examining psychological reactions to terrorist attacks in the aftermath of the September 11, 2001 (9/11) terrorist attacks, Schlenger et al. (2002) demonstrated that those exposed to a traumatic event are at high risk of suffering from post-traumatic stress disorder. In Korea, one of the nation's worst maritime disasters occurred in April 2014, and most of the 304 victims of the Sewol disaster were high school students. The entire nation was overwhelmed with grief and concern for the victims and their families, who were devastated and fragile. Whereas victims and families in deep mourning merit care and attention, relatively little attention has been paid to understanding the grief transition that the general population, especially those in affected communities who commiserate with victims and victims' families, experiences after a tragedy. In fact, people tend to share their emotions with others, and this sharing tends to be positively associated with physical proximity (LeBon, 1985), group membership (Seger et al., 2009), and relationships between individuals (Hess & Fischer, 2013). In defining the attributes needed for building a sense of community, McMillan and Chavis (1986) suggested the importance of shared emotional connectedness, which can be facilitated by the frequency and quality of interactions. Sharing emotions with others can result in a convergence of emotions, as moods are transferred from person to person. Interactions in neighborhoods, schools, and workplaces increase closeness among individuals, simultaneously increasing the likelihood of influencing the attitudes and behaviors of others.

In Korea, the *Sewol* disaster caused little financial damage amid the tragic loss of human life. Collectively, however, distressed emotions dragged on consumer sentiment. In the prevailing atmosphere of mourning, credit-card spending decreased significantly, as people canceled leisure activities, and companies postponed marketing activities. In the week following the sinking, credit-card consumption on apparel dropped by 4.3 percent and on leisure activities by 3.8 percent, compared with the same week in the previous year, according to the country's credit finance association. Nevertheless, it is difficult to observe the direct effects of the tragedy at the aggregate level. For this reason, investigating consumer behavior at the individual level is important to understand the economic effects of the tragedy and to prepare for grief transition in the domain of consumer behavior.

Using account-level credit-card data, this chapter investigates the effects of a tragic event on consumption, as well as whether the physical distance between residences and victims matters in determining the effects on credit-card consumption. A regression model with fixed effects revealed that the *Sewol* disaster can be linked to a reduction in credit-card spending, on average, of 4 percent on the part of victims' families or neighbors who lived closest to victims, and of 1.6 percent on the part of neighbors who lived in the same city as victims. Given that the average monthly spending by families and neighbors in close proximity was $561 before the tragedy, if we assume that the effect lasts for one year, it is equivalent to reducing annual spending by $269 per person. The reduction in spending was particularly significant among females and credit-card holders in the 40s–50s age group.

II. The *Sewol* Disaster

2.1. The Disaster

On the morning of April 16, 2014, the *Sewol* sank off the southwestern coast of South Korea. The ship was carrying 476 passengers, including 325 secondary school students from Danwon High School who were on a field trip to the resort island of Jeju. Of these passengers, 172 were rescued, and 304 passengers and crew members died. The sinking's principal, official cause cited was a sudden turn of the vessel, which became uncontrollable as the ship listed. Overloading and improper storage also elevated the danger of listing and capsizing.[2] What devastated parents and the nation was the crew's failure to evacuate passengers. As the ferry began sinking, the crew

[2] The *Sewol* was restricted to carrying a maximum of 987 tons of cargo, but sank with 3,608 tons on board.

repeatedly instructed passengers to remain in their cabins until rescuers could arrive. While passengers did as instructed, the captain and crew members fled the sinking ship. The broadcast revealed that crew members were among the first to be rescued, and that some were even holding beers while waiting to be rescued. Widespread criticism rained down not only on the crew, but also on the Korean government's incompetent and lackluster rescue operation, sparking nationwide anger and grief and resulting in loss of trust in the government. Only passengers who jumped into the water or stayed near the top of the vessel survived, but most who stayed in the cabins perished. Meanwhile, victims' families anxiously waited for word of their missing children at the harbor nearest to where the disaster occurred. Despite its failed rescue operations, the government provided neither a sincere apology nor an explanation of the systematic problems that led to the disaster. In the weeks and months following the disaster, citizens mourned collectively for the missing, and they collected donations for victims' families. Yellow ribbons appeared all over the country as symbols of hope, with images spreading across social media. On the first anniversary of the *Sewol* disaster, the families and thousands of other citizens gathered for a rally to demand a full investigation of the disaster, as well as regulations to prevent future accidents.

2.2. Understanding Affective States in a Neighborhood

The unprecedented disaster elicited public trauma. In the aftermath of the disaster, keywords indicating emotional agitation -- such as "anger," "suicide," and "sadness" -- increased substantially on daily Twitter feeds (Woo et al., 2015). The act of sharing emotions occurred not only over social media, but also in the neighborhoods where people consoled bereaved families. News reports indicated that, following the tragedy, post-traumatic stress disorder was found not only among survivors, but also among divers who conducted rescue operations and volunteers who helped devastated parents.[3] Consequently, the sharing of emotions generated a convergence of emotions as the moods of presenters influenced the affective states of respondents, a phenomenon known as *emotional contagion*, "a process in which a person or group influences the behavior of another person or group through the conscious or unconscious induction of emotional states and behavioral attitudes" (Schoenewolf, 1990). Emotional contagion is a way of adapting to social information whereby people compare their moods with those of others', then behave in what seems to be an acceptable way for a given situation (Nakahashi & Hisashi, 2015). Transfer of emotions is known to occur more often with negative than positive emotions, as people pay more attention to negative emotions that are often threat-related (Öhman et al., 2001). Emotional contagion has been found in many experimental studies in which respondents mimic the facial expressions of presenters (Hess & Blairy, 2001), and it follows emotional states that are like those of presenters (Laird et al., 1994; Lundqvist & Dimberg, 1995; Neumann & Strack, 2000). As such, neighbors who are likely to encounter victims or their family members face-to-face are more likely influenced emotionally by the bereaved expressing their pain over losing children.

Transfer of emotions has been recognized by many researchers. Schlenger et al. (2002) noted that those living in New York City during the 9/11 terrorist attack there tended to suffer more acutely from post-traumatic stress disorder than individuals

[3] http://www.koreatimes.co.kr/www/news/nation/2016/06/116_207414.html

living in the rest of the country. Four years earlier, Bull et al. (2003) found an increasing pattern of service requests at grief-related organizations during the three weeks after Princess Diana's death. Omdahl and O'Donnell (1999) used questionnaires administered to nurses at two hospitals on the emotional labor required of service providers. They examined whether empathy-related variables such as emotional contagion, empathic concerns for patients, and responsiveness in conversations contributed to nursing stress and burnout. They found that the combination of the three variables caused stress for nurses, and that emotional contagion, in particular, was the most significant predictor of emotional exhaustion.

Several researches have found evidence of a carryover effect from emotions on consumption. For example, some studies have presented evidence that pleasant weather conditions can improve individuals' self-assessments of mood – and can even influence tipping behavior at restaurants (Cunningham,1979; Rind & Strohmetz, 2001). Cryder et al. (2008) demonstrated in an experiment that there is a positive relationship between sadness and the amount of money spent to purchase a commodity, and that this relationship is partly explained by a level of self-focus. In Korea, the *Sewol* disaster triggered emotional agitation in the public, which was subsequently reflected in dampened consumer sentiment.[4] Although the disaster caused little financial damage amid the tragic loss of human life, collective emotional distress followed, dragging on consumer sentiment and thereby generating a potential threat to the economy. Indeed, the 9/11 terrorist attacks generated localized economic effects, especially in directly targeted areas such as New York City and Washington, D.C.

[4] http://blogs.wsj.com/korearealtime/2014/05/09/ferry-tragedy-hits-consumer-spending/

(Makinen, 2002). Similarly, threats to the economy can be significant among neighbors who are likely to bond strongly with victims, then influence credit-card spending. In this chapter, I tested the following hypotheses:

H0: Monthly credit-card spending and the amount spent per transaction will not change for the bereaved and neighbors after a disaster.

H1: Monthly credit-card spending and the amount spent per transaction will change for the bereaved and neighbors after a disaster.

The rest of the chapter proceeds as follows. In Section III, I describe the data sources and regression variables. Section IV estimates the models and presents the results. Section V tests for robustness, and Section VI concludes the study.

III. Data Description

This study employs account-level credit-card data from a large card issuer in Korea from April 2013 through May 2014. The data include information on 1.6 million accounts, for a total of 22.7 million year-month observations of credit-card behaviors, such as monthly credit-card spending, number of credit-card transactions, and balances of revolving credit. Due to computational difficulty, the study utilizes a large subset of individuals who share the most common surname in Korea, *Kim*, which generally accounts for 22% of all Korean households, according to the Korean Statistical Information Service. Because our data come from a large credit-card company, and cardholders are randomized by a common surname, individuals in our dataset should be representative of all cardholders in Korea. This study uses a subset of the original data by restricting the sample to cardholders whose total spending is greater than zero and whose credit-card ownership extends past the date of the tragedy. Each account represents a single monthly statement for all cards issued by the company, as cardholders may own multiple cards from the same company.

The sample data consist of three types of non-traceable cardholder information. First, there is transactional information for each cardholder that includes total balance, number of credit-card transactions, past due balance, revolving credit, installment credit, and outstanding debt. The card issuer has provided information by calendar month, which makes transactional information measured at month's end available. Total balance is the debt principal, consisting of monthly credit-card transactions from purchases and cash advances. It is the closing balance at the end of each month and, therefore, differs from payment due. While payment due includes debt principal in the billing cycle, incurred interest fees, past due balances from previous billing periods, and a portion of debts from deferred debts, the total balance is the monthly debt principal, which does not include deferred debts or extra fees. Since mandatory fees incurred in payments due do not necessarily indicate voluntary cardholder spending, this study uses total balance as a measure of credit-card spending.

The number of credit-card transactions indicates the number of monthly credit-card purchases. Past due balance is the debt principal that has not been paid as of its due date. Cardholders have two options for carrying balances. The first involves revolving credit, in which payments are open-ended and decided at the time of payment. With revolving credit, the amount of the debt payment can be different each month. The second option is installment credit, in which payments are close-ended and decided at the time of purchase. To use installment credit, cardholders typically set a specific time for full redemption and pay off a debt in equal amounts over the course of a set period. In many countries, installment credit takes the form of loans for large investments, such as auto loans and mortgages. In Korea, however, installment credit is widely used by cardholders for products with prices ranging from $100 to $1,000, thanks to competitive interest rates.[5]

Outstanding debt consists of portions of the debt principal that are excluded from payments due in the current month and deferred through revolving or installment credit from previous billing periods.[6] The data also contain cardholder credit limits that are observed by card issuers that use internal and external sources to evaluate cardholder credit-worthiness. Finally, the data include demographic information on cardholders such as gender, age, and postal codes. A postal code in South Korea typically consists of six digits:[7] The first digit denotes the province, the second denotes indicates the city or county, the third denotes the district of the city, the fourth denotes the sub-municipal level of the city, and the rest denote the delivery address. To protect the identity of cardholders, however, the card issuer provided only up to five digits of postal codes, but this enabled me to determine and observe each cardholder's city of residence. Although the sample data for this study provided very detailed tracking information pertaining to cardholders' borrowing behaviors and an exceptionally large sample size, increasing the reliability of the results, they are subject to limitations. Because of the policy constraint, the card issuer restricted access

[5] Interest charges for installment credit range from 4% to 21%, whereas those for revolving credit range from 6% to 24% as of March 2016. It is also quite common for card issuers and affiliated merchants to offer interest-free installment plans for up to three months to boost sales.
[6] Outstanding debt is uncharged debt by the end of a month and does not include past due balances.
[7] It consisted of six digits until August 2015, then changed to five digits.

to some important information, such as cardholder income, marital status, and interest rates. Information regarding cardholder income can be particularly important, as changes in income can affect credit-card spending significantly. In this chapter, I used a fixed-effect model to control for unobservable individual heterogeneity.

IV. Methodology

4.1. Cardholders in Three Areas

This study investigates consumer reactions to an "exogenous shock," the *Sewol* disaster, and measures how changes in credit-card consumption are associated with physical proximity to victims or their families. Using ZIP codes in the dataset, I found cardholder residences at the sub-municipal level and categorized them into three areas at the time of the disaster. The first area is the smallest sub-municipal level of a city, which I labeled *Bereaved*, where Danwon High School and the homes of missing students are located. The addresses of missing students can be inferred only from newspaper accounts, which reported that 149 students from the *Bereaved* area were missing following the disaster.[8] Although victims may have lived in other locations as well, I believe that most victims lived in *Bereaved* for the following two reasons. First, students in general attend schools closest to their residences, so most of the students likely lived in or near the area where Danwon High is located.[9] Second, among the 261 missing students who were later found dead, more than half were reported as residing in *Bereaved*. Certainly, not all the cardholders living in *Bereaved* are families

[8] http://m.kyeongin.com/view.php?key=848801

[9] There are 24 high schools in Ansan, the city where *Bereaved* is located. The area of the city is 58 square miles, and there were 35,926 high school students as of 2010, according to the National Statistical Service.

of victims, but it is highly likely that most mourning families and neighbors lived in *Bereaved*. There are approximately 71,000 residents in an area of about 2 square miles.

The second area, labeled *Neighbor*, is the City of Ansan, where *Bereaved* is located and where 695,000 residents live. The area of *Neighbor* is approximately 58 square miles, in which 23 sub-municipal units exist, excluding *Bereaved*. Because *Bereaved* is located at the center of this city, *Bereaved* residents normally can reach any location in *Neighbor* in a 20-minute-or-shorter drive. *Neighbor* is located approximately 18 miles southwest of Seoul, South Korea's capital. Locational advantage has made *Neighbor* a government-planned city designed to decentralize the population and factories that had been concentrated in the capital city. As such, the economy in *Neighbor* is driven mainly by manufacturing industries. The third area, labeled *Distance*, consists of neighboring communities and cities beyond *Neighbor*. It usually takes more than 20 minutes to drive from *Bereaved* to any location in *Distance*, which has an area of roughly 114 square miles. Figure 2.1 provides a description of each area.

Figure 2.1: Description of Three Areas

Area	Description	Details	Miles from *Bereaved*
Bereaved	Cardholders in *Bereaved*	2 smallest units near Danwon High school	-
Neighbor	Cardholders in *Neighbor*	City where Danwon High School is located	≤ 10
Distance	Cardholders in *Distance*	Neighboring districts and units beyond *Neighbor*	$10 < x \leq 20$

4.2. Fixed-Effects Regressions

4.2.1. Descriptive Statistics

Table 2.1 presents descriptive statistics on cardholders in the sample. Column (1) in Table 2.1 exhibits the mean and standard deviation for the entire sample population. The columns 2 to 4 display the means and standard deviations of cardholders who are segmented into the following three areas: *Bereaved* in column (2), *Neighbor* in column (3), and *Distance* in column (4). Others in column (5) reside elsewhere than *Bereaved*, *Neighbor*, or *Distance*. Panel A of Table 2.1 presents demographic information on cardholders, and panel B and panel C present the means of transactional information before and after the *Sewol* disaster, respectively. *Gender* indicates the ratio of male to female cardholders, and *Age* represents the average age of cardholders in the group. *Credit Limit ($)* is the average dollar amount of the credit limit provided by the card company, and *Monthly Usage* is the average number of credit-card swipes per month. *Spending ($)* is the average total balance per month and includes cash advances and all transactions involving a credit card. *Cash Advance ($)* is the average of monthly cash advances, and *Install & Revolving ($)* is the average of monthly credit-card spending, which cardholders assign to future repayment by using either revolving or installment credit. *Outstanding Debt ($)* consists of unpaid credit-card debt, but does not include past due balances or fees. *Past Due Balance ($) > 0* is the average of past due balances that are greater than zero.

Table 2.1: Descriptive Statistics

		By Area			
	All	*Bereaved*	*Neighbor*	*Distance*	*Rest of the Country*
	(1)	(2)	(3)	(4)	(5)
Panel (A). Demographic Information					
Gender (male=1)	0.50	0.49	0.49	0.50	0.50
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
Age	45.6	44.7	45.0	45.4	45.7
	(11.8)	(11.2)	(11.1)	(11.5)	(11.8)
Panel (B). Before Sewol Ferry Disaster					
Credit Limit ($)	4,939	3,975	4,555	4,958	4,945
	(4,402)	(3,344)	(3,890)	(4,268)	(4,413)
Monthly Usage	11	9	11	12	11
	(15.3)	(12.0)	(13.6)	(15.0)	(15.3)
Spending ($)	614	561	619	621	614
	(1,234)	(1,026)	(1,479)	(1,225)	(1,231)
- Cash Advance ($)	111	115	111	111	111
	(588)	(470)	(548)	(569)	(589)
- Install & Revolving ($)	334	312	337	343	334
	(844)	(635)	(775)	(799)	(847)
Outstanding Debt ($)	969	964	1,000	984	968
	(1,816)	(1,546)	(1,762)	(1,790)	(1,818)
Past due Balance ($)>0	820	589	871	790	821
	(1,786)	(1,119)	(1,779)	(1,913)	(1,783)
Panel (C). After Sewol Ferry Disaster					
Credit Limit ($)	4,917	3,961	4,525	4,932	4,923
	(4,405)	(3,342)	(3,882)	(4,263)	(4,417)
Monthly Usage	11	9	11	12	11
	(15.5)	(12.8)	(14.1)	(15.4)	(15.5)
Spending ($)	581	528	582	589	581
	(1,236)	(974)	(1,153)	(1,202)	(1,239)
- Cash Advance ($)	103	112	102	103	103
	(561)	(512)	(523)	(546)	(562)
- Install & Revolving ($)	310	285	312	319	309
	(772)	(586)	(728)	(716)	(774)
Outstanding Debt ($)	938	928	961	953	938
	(1,823)	(1,553)	(1,711)	(1,795)	(1,826)
Past-Due Balance ($)>0	955	738	993	880	957
	(2,023)	(1,413)	(2,235)	(2,406)	(2,010)
Number of Individuals	1,637,858	2,163	22,193	41,136	1,572,366
Number of Observations	22,787,729	30,114	308,907	572,604	21,876,104

Descriptive statistics shown in column (2) of Table 2.1 indicate that the credit-card activities of cardholders in *Bereaved* tend to be at lower levels than those of cardholders in the rest of the country in terms of average credit limits ($3,975), monthly usage (9), and credit-card spending ($561). The disaster dampened consumer sentiment somewhat, as reflected in credit-card spending. Average spending decreased for the entire sample population from $614 to $581 (panel C in column [1]). Moreover, panel C in column (2) shows that the decrease in credit-card spending was substantially greater among cardholders in *Bereaved* (from $561 to $528) and cardholders in *Neighbor* (from $619 to $582). Changes in spending after the disaster were similar between cardholders in *Distance* (from $621 to $589) and others (from $614 to $581).

4.2.2. Fixed-Effects Regression

This study examined the effect of shared emotions on credit-card debt. Let Y_{it} be the dependent variable for individual *i* at the end of month *t*. The model in this study used four dependent variables as measures of emotional changes following the disaster. The first dependent variable is the dollar amount of the total balance denoted as *ln(Total Spending)*, which is the log-debt principal from purchases and cash advances. To specify the source of changes, I separated the components of *ln(Total Spending)* and used them as the second and third dependent variables. The second dependent variable considered the dollar amount of credit-card purchases, denoted as *ln(Card)*, which is the log-debt principal from credit-card transactions, excluding cash advances. The third dependent variable considered the dollar amount of cash advances, denoted as *ln(Cash)*, which is the log-debt principal from cash advances, excluding credit-card transactions. Finally, there is log spending per usage, denoted as *ln(Spending Per Swipe)*, which is the monthly credit-card balance divided by the number of uses. *ln(Spending Per Swipe)* shows the size per transaction—the higher the value, the more expensive the product. It demonstrates a cardholder's tendency to buy expensive goods. Standard errors are clustered by mean credit-card usage, which is the average credit-card usage for the total study period. After averaging credit-card usage, I used an integer of a mean for clustering. All three dependent variables share the following regression model:

$$\begin{aligned} \boldsymbol{Y_{it}} &= \boldsymbol{\alpha_i + \delta X_{i,t} + \gamma_1 (Beraeved_i * Post_t) + \gamma_2 (Neighbor_i * Post_t)} \\ &\quad \boldsymbol{+ \gamma_3 \, (Distant\_Neighbor_i * Post_t) + \varepsilon_{it}} \end{aligned}$$

The regression model uses identical explanatory variables, X_{it}, which consist of the following four variables: (a) the log credit limit of cardholders, *ln(Credit Limit)*; (b) the log number of monthly transactions, *ln(Usage)*; (c) the log of the previous month's outstanding debt, *Lag_ln(Outstanding)*; and (d) the log of the past due balance *ln(Past Due)*. The credit limit ranges from $0 to $200,000 and is provided by the card company, which uses internal and external sources to evaluate a cardholder's credentials. Number of uses is the number of monthly credit-card transactions and includes purchases and cash advances. Lag outstanding debt is the previous month's uncharged debt balance, a portion of which is rolled over into payments due the following month. Past due balances are unpaid debts that were charged for repayment within a certain date. *Bereaved* is a dummy variable that equals 1 if a cardholder lives in *Bereaved*, the closest physical proximity to victims' residences. *Neighbor*, a dummy variable that equals 1 if a cardholder lives in *Neighbor* and zero otherwise, involves cardholders living in the same city as cardholders in *Bereaved*, but not in *Bereaved*. *Distance*, a dummy variable that equals 1 if a cardholder lives in *Distance* and zero otherwise, consists of cardholders who live in neighboring sub-municipal units or districts beyond *Neighbor*. *Post* is a dummy variable that equals 1 if a transaction occurs after March 31, 2014, and zero otherwise. Because the card issuer has provided information by calendar month, *Post* may include some transactions that occurred before April 16, 2014, when the *Sewol* disaster took place. Individual and time dummies are included to control for individual heterogeneity and time trends.

4.2.3. Results of Fixed-Effects Regressions

This section presents the results of fixed-effects regression, with t-statistics in parentheses. The dependent variables are in column (1) of Table 2.2, *ln(Total Spending)*; in column (2), *ln(Card)*; in column (3), *ln(Cash)*; and in column (4), *ln(Spending Per Swipe)*. The results shown in column (1) indicate that, after the disaster, credit-card spending on the part of cardholders in *Bereaved* decreased by 4 percent more than spending by cardholders in the rest of the country, as denoted by a statistically significant coefficient of -0.04 (t-statistics=-2.38) in *Bereaved_Post*. Average spending on the part of cardholders in *Bereaved*, which was $561 before the disaster, is equivalent to a reduction in annual spending of $269 per person. The effect of the disaster on credit-card spending became less acute among cardholders who live in the same city, by -1.7 percent, as denoted by a statistically significant coefficient of

-0.017 (t-statistics=-3.59) in *Neighbor_Post*. A negative coefficient of *Neighbor_Post* implies, however, that the affiliation from living in the same city somehow made people compassionate about their neighbors' tragedies. Such affiliated compassion disappears for cardholders living in *Distance*, as denoted by a coefficient of -0.002 (t-statistics=-0.35) in *Distance_Post*.

Table 2.2: Results from Fixed-Effects Regression

	Y=ln(Total Spending) (1)	ln(Card) (2)	ln(Cash) (3)	ln(Spending Per Swipe) (4)
ln (Credit Limit)	0.228***	0.165***	0.148***	0.269***
	(11.06)	(8.06)	(15.81)	(36.81)
ln (Usage)	1.748***	1.770***	1.169***	0.146***
	(12.71)	(13.73)	(38.67)	(2.63)
Lag ln (Outstanding)	-0.006	-0.012**	0.048***	0.007**
	(-0.96)	(-2.20)	(10.71)	(2.28)
ln (Past Due)	-0.036***	-0.019***	0.011	-0.035***
	(-18.06)	(-7.32)	(0.89)	(-37.45)
Bereaved_Post	**-0.040****	**-0.048*****	**-0.013**	**-0.030****
	(-2.38)	**(-3.43)**	**(-0.38)**	**(-2.20)**
Neighbor_Post	**-0.017*****	**-0.022*****	**-0.023***	**-0.013*****
	(-3.59)	**(-4.91)**	**(-1.85)**	**(-3.21)**
Distance_Post	**-0.002**	**-0.005**	**0.007**	**-0.005**
	(-0.35)	**(-1.16)**	**(1.02)**	**(-1.30)**
r2	0.526	0.559	0.090	0.022
N	18.5 mil	18.5 mil	18.5 mil	18.5 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

T-statistics are reported in parentheses, with a statistical significance for $p < 0.1$, $p < 0.05$ and $p < 0.01$ denoted by *, **, and ***, respectively.

Moreover, the results shown in column (2) indicate that the reduction in total spending was mainly in credit-card purchases, as denoted by a statistically significant coefficient of -0.048 (t-statistics=-3.43) in *Bereaved_Post*. It is, however, hard to tell whether the tendency to withdraw cash also was affected by the disaster, as denoted by a coefficient of -0.013 (t-statistics=-0.38) in *Bereaved_Post* in column (3). Given that parents had to rush to the harbor nearest to the accident area, it is possible that their unexpected trips to the harbor caused them to withdraw cash for emergency purposes.

For cardholders living in the same city, both credit-card spending and cash advances decreased substantially, with a statistically significant coefficient of -0.022 (t-statistics=-4.91) for credit-card spending and -0.023 (t-statistics=-1.85) for cash advances in *Neighbor_Post*. In column (4), the results reveal that the tendency to purchase expensive goods also decreased by 3 percent among cardholders in *Bereaved*, denoted by a statistically significant coefficient of -0.030 (t-statistics=-2.20). Similarly, cardholders in *Neighbor* also cut their spending on expensive goods by 1.3 percent more than cardholders in the rest of the country, as denoted by a statistically significant coefficient of -0.013 (t-statistics=-3.21) in *Neighbor_Post*.

4.3. Difference-in-Differences Estimations

4.3.1. Matching Method

In this section, I estimate the mean difference in differences using matched datasets. Before running the difference-in-differences estimations, I created three datasets based on five averaged covariates: age, credit limits, spending, number of transactions, and uncharged debt balances. After averaging the five covariates, I estimated a propensity score based on the average covariates using a probit model. Then I kept five decimal places of a propensity score and matched cardholders in *Bereaved* with those in *Non-Bereaved* who have the same propensity scores to five decimal places for the first matched dataset. *Bereaved* is defined as the neighborhood located closest to victims' residences, and *Non-Bereaved* includes the area outside of *Bereaved*. For the second dataset, I matched cardholders in *Neighbor* with cardholders in *Non-Neighbor* who have the same propensity scores to five decimal places. *Neighbor* is defined as the city of the victims' residences, Ansan, but it does not include *Bereaved*, and *Non-Neighbor* is the area outside of *Neighbor*. Finally, for the third matched dataset, I matched cardholders in *Distance* with cardholders in *Non-Distance*. *Distance* includes cities near *Neighbor* that are neither *Bereaved* nor *Neighbor*, and *Non-Distance* includes the rest of the country that is outside of *Distance*. The matching order is randomized, and pairing groups are used more than once as a match.

Table 2.3 presents descriptive statistics after matching. Three columns show the means and standard deviations: the first column for *Bereaved* and *Non-Bereaved*, the second column for *Neighbor* and *Non-Neighbor*, and the third column for *Distance* and *Non-Distance*. As seen in Table 2.3, the means of the matched variables in particular — age, credit limits, spending, number of transactions, and uncharged debt balances — became similar after matching, compared with the means in the descriptive statistics shown in Table 2.1.

Table 2.3: Descriptive Statistics after Matching

	Bereaved	*Non-Bereaved*	*Neighbor*	*Non-Neighbor*	*Distance*	*Non-Distance*
	(1)		(2)		(3)	
Gender (male=1)	0.50	0.49	0.50	0.49	0.50	0.49
	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)
Age	45.5	45.5	45.5	45.5	45.9	45.6
	(10.9)	(11.8)	(11.1)	(11.8)	(11.7)	(11.8)
Credit Limit ($)	4,694	4,609	4,829	4,748	4,896	4,887
	(3,715)	(3,734)	(3,980)	(3,956)	(4,225)	(4,321)
Monthly Usage	11	11	11	11	11	11
	(13.3)	(14.4)	(14.2)	(14.9)	(14.0)	(14.2)
Spending ($)	600	579	600	583	583	584
	(1,018)	(1,117)	(1,055)	(1,102)	(1,107)	(1,101)
Cash Advance ($)	113	105	99	101	105	100
	(485)	(542)	(495)	(518)	(525)	(504)
Revolving ($)	309	294	316	299	320	321
	(596)	(724)	(699)	(724)	(746)	(773)
Outstanding Debt($)	956	919	953	921	931	934
	(1,484)	(1,688)	(1,597)	(1,665)	(1,710)	(1,728)
Past Due ($)>0	643	784	797	783	824	830
	(1,208)	(1,590)	(1,618)	(1,679)	(2,083)	(1,788)
Number of Individuals	1,590,810	1,590,810	1,591,825	1,591,825	1,585,632	1,585,632
Number of Obs.	22,149,331	22,130,270	22,159,955	22,145,775	22,069,368	22,060,503

4.3.2. Difference-in-Differences Estimations

Using a matched dataset, I estimated difference in differences by taking the means of credit-card debt before and after the disaster. Dependent variables are the same as those used in the fixed-effects regression. Credit-card debt includes *ln(Total Spending), ln(Card), ln(Cash),* and *ln(Spending Per Swipe)*. Let $\overline{Y_t}$ be the mean of credit-card debt and *t* be the periods that equal 0 for the pre-treatment period, with 1 for the post-treatment period. *AREA* indicates *Bereaved* for the first dataset, *Neighbor* for the second dataset, and *Distance* for the third dataset. There are three difference-in-differences estimations taking the following form:

$$DD = [(\bar{Y_1}|AREA) - (\bar{Y_0}|AREA)] - [(\bar{Y_1}|Non\_AREA) - (\bar{Y_0}|Non\_AREA)]$$

In Table 2.4, I present results from difference-in-differences estimations in three columns: those for *Bereaved* and *Non-Bereaved* are shown in column (1), those for *Neighbor* and *Non-Neighbor* are shown in column (2), and those for *Distance* and *Non-Distance* are shown in column (3). In each main column, I present the average credit-card debt in period *t* in sub-columns (i) and (ii) and the difference-in-differences estimations in sub-column (iii). Panels A, B, C, and D display average levels and changes in *ln(Total Spending)*, *ln(Card)*, *ln(Cash)*, and *ln(Spending Per Swipe)*, respectively. For credit-card debt in each panel, I averaged the non-missing values of credit-card debt by *t* and *AREA*, and subtracted the results shown in column (i) from the results shown in column (ii) to estimate difference in differences. For example, for *ln (Total Spending)* in panel A, I averaged the non-missing values of *ln(Total Spending)* by *t* and *AREA*, then subtracted the results shown in column (i) from the results shown in column (ii) to estimate difference in differences.

Table 2.4 summarizes the results of difference-in-differences estimations. I found that the overall economic significance in difference-in-differences estimations tended to diverge from that found in the regression model, but was consistent with that obtained from the regression model in terms of signs. Moreover, the results of difference-in-differences estimations revealed a clearer relationship between the effect of the disaster and the affiliations of those living near the victims. For example, panel A shows that, after the *Sewol* disaster, average total spending by cardholders in

Bereaved decreased by 1.1 percent relative to that of cardholders in *Non-Bereaved*, which was less than the 4 percent decrease in total spending found in the regression model. However, comparing the results shown in column (1) with those shown in column (2) and column (3) of panel A shows that the effect of the disaster on credit-card spending weakens among cardholders who live in the same city, by -0.2 percent, and eventually becomes positive among cardholders who live in *Distance*. Similarly, panel B shows that, after the *Sewol* disaster, average credit-card spending by cardholders in *Bereaved* decreased by 1.2 percent relative to that of cardholders in *Non-Bereaved*, which is less than the 4.8 percent decrease in credit-card spending found in the regression model. However, comparing results shown in column (1) with those shown in column (3) of panel B reveals a strong positive trend in the relationship between the effect of the disaster and affiliation with victims.

Table 2.4: Difference-in-Differences Estimations

	Bereaved vs. Non-Bereaved (1)				*Neighbor vs. Non-Neighbor* (2)				*Distance vs. Non-Distance* (3)		
	Before Treat (i)	After Treat (ii)	Difference (ii)-(i)		Before Treat (i)	After Treat (ii)	Difference (ii)-(i)		Before Treat (i)	After Treat (ii)	Difference (ii)-(i)
Panel A: Average ln(Spending)											
Bereaved	4.738	4.535	-0.203***	*Neighbor*	4.668	4.475	-0.192***	*Distance*	4.559	4.376	-0.183***
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Non-Bereaved	4.510	4.318	-0.192***	*Non-Neighbor*	4.526	4.335	-0.190***	*Non-Distance*	4.526	4.334	-0.192***
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Difference	0.228***	0.217***	**-0.011*** **	*Difference*	0.142***	0.140***	**-0.002** **	*Difference*	0.033***	0.042***	**0.009*** **
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Panel B: Average ln(Card)											
Bereaved	4.554	4.361	-0.192***	*Neighbor*	4.514	4.328	-0.186***	*Distance*	4.400	4.227	-0.173***
	[0.001]	[0.001]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Non-Bereaved	4.349	4.169	-0.180***	*Non-Neighbor*	4.367	4.188	-0.179***	*Non-Distance*	4.368	4.188	-0.181***
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Difference	0.205***	0.193***	**-0.012*** **	*Difference*	0.148***	0.140***	**-0.007*** **	*Difference*	0.032***	0.039***	**0.007*** **
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Panel C: Average ln(Cash)											
Bereaved	1.471	1.378	-0.093***	*Neighbor*	1.229	1.141	-0.088***	*Distance*	1.141	1.078	-0.063***
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Non-Bereaved	1.131	1.071	-0.060***	*Non-Neighbor*	1.121	1.062	-0.059***	*Non-Distance*	1.123	1.062	-0.061***
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Difference	0.341***	0.308	**-0.033*** **	*Difference*	0.108***	0.078***	**-0.029*** **	*Difference*	0.018***	0.016***	**-0.002** **
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.001]
Panel D: Average ln(Spending Per Swipe)											
Bereaved	3.648	3.590	-0.058***	*Neighbor*	3.621	3.590	-0.031***	*Distance*	3.575	3.553	-0.021***
	[0.000]	[0.001]	[0.001]		[0.000]	[0.001]	[0.001]		[0.000]	[0.001]	[0.001]
Non-Bereaved	3.597	3.583	-0.014***	*Non-Neighbor*	3.596	3.581	-0.015***	*Non-Distance*	3.602	3.587	-0.015***
	[0.000]	[0.001]	[0.001]		[0.000]	[0.001]	[0.001]		[0.000]	[0.001]	[0.001]
Difference	0.050***	0.007***	**-0.043*** **	*Difference*	0.025***	0.009***	**-0.016*** **	*Difference*	-0.028***	-0.034***	**-0.006*** **
	[0.001]	[0.001]	[0.001]		[0.001]	[0.001]	[0.001]		[0.001]	[0.001]	[0.001]

V. Robustness Tests

To ensure that the results shown in Table 2.2 are not sensitive to alternative specifications, Appendix 2 presents the results of robustness tests. I used alternative periods, gender, credit score, and age, then examined a fixed-effect regression with standard errors clustered by mean credit-card usage. After averaging the credit-card usage for the total study period, I used an integer of a mean for clustering. In Table 2A, I present the results of the robustness tests specified by alternative periods. The results for the dependent variable *ln(Spending)* are shown in the first column, the results for *ln(Card)* are shown in the second column, the results for *ln(Cash)* are shown in the third column, and the results for *ln(Spending Per Swipe)* are shown in the fourth column. For this specification, I used the period running from October 2013 through May 2014. The results in Table 2A show that the orders of the coefficients remained consistent between cardholders in *Bereaved* and those in *Neighbor*, in that credit-card spending decreased by 2.9 percent among the former and by 1.3 percent among the latter when compared with spending in the six months before the disaster. Results shown in columns (2) through (4) show that the orders of the coefficients remained consistent between cardholders in *Bereaved* and those in *Neighbor* when the dependent variable is *ln(Card)*, *ln(Cash)*, or *ln(Spending per Swipe)*. Moreover, because my sample dataset contains information up to 1.5 months after the disaster, and because examining the persistence of the effect requires a longer duration, this study does not investigate the persistence of the effect, leaving that question to future research.

In Table 2B, I test whether the results are differentiated by gender by segmenting cardholders by gender. Results shown in Table 2B indicate that affective reactions in terms of credit-card spending occurred mostly in women. For example, column (1) of Table 2B shows that female cardholders in *Bereaved* cut their total spending by 6 percent more than female cardholders in the rest of the country, whereas it is hard to tell whether total spending for male cardholders in *Bereaved* was statistically different from that of male cardholders in the rest of the country. The gender differences shown in column (1) are partly explained by gender differences in coping with emotional distress, as found in previous research indicating that women tend to be more vulnerable to traumatic events or emotional distress than men (Olff et al., 2007). For cardholders living in the same city, however, the reduction in spending was similar for men and women, as indicated by statistically significant coefficients of -0.016 (t-statistics=-2.03) for men and -0.019 (t-statistics=-2.33) for women in *Neighbor_Post*. In Table 2C, I tested a specification by grouping cardholders by mean credit score. After averaging credit scores for the entire sample period, I segmented cardholders into the bottom 25th percentile and the top 25th percentile. Results shown in Table 2C indicate that total spending for cardholders in *Neighbor* whose average credit score is in the bottom 25th percentile tend to be more heavily swayed by the tragic event in the neighborhood than cardholders whose average credit score is in the top 25th percentile.

Finally, I averaged the age of cardholders into a 20s–30s age group, a 40s–50s age group, and a 60-and-above age group, then compared the credit-card behaviors of cardholders across generations in Table 2D. Results shown in Table 2D indicate that cardholders in *Bereaved* who are in the 40s–50s age group were most heavily influenced by the tragic event. Given that parents whose children are in high school are presumed to be, on average, in their 40s, a substantial reduction in spending on the part of members in the 40s–50s age group seems reasonable.

VI. Conclusion

In this chapter, I found that the *Sewol* disaster caused negative emotions in the public that were simultaneously reflected in credit-card spending. The link between tragic events and credit-card spending was particularly strong among neighbors who lived near bereaved families, gradually attenuating among cardholders living at greater distances. This study suggests that substantial decreases in credit-card spending among the closest neighbors were in part due to neighborhood affiliations that generated transfer of sad emotions as neighbors interacted with the bereaved families. Moreover, the disaster affected not only the total amount of credit-card spending, but also the amount per transaction, suggesting that the tendency to buy expensive products also decreased due to the atmosphere of mourning. Additionally, a substantial reduction in credit-card spending among female neighbors revealed the likelihood that women are more vulnerable to post-traumatic stress disorder, which is consistent with previous research that investigates gender differences in stress disorders (Olff et al., 2007). The localized effects in the neighborhood following the disaster were also consistent with the findings of previous studies (Garner, 2002; Makinen, 2002). Whereas past studies focused on the effect of disasters in terms of psychological symptoms, consumer confidence, or economic effects at the aggregate level, this study explored the economic effects at an individual level over time, allowing for a better understanding of behavioral dynamics in greater detail.

Many studies also have noted that the economic effects of a disaster such as 9/11 are short-lived (Garner, 2002; Makinen, 2002). However, the persistence of the effects following the *Sewol* disaster was not measured in this chapter due to limitations in the dataset, which opens up opportunities for future research. This study uses consumption patterns to measure emotional changes in the aftermath of the disaster. The findings reported in this study may help policymakers and marketers find a new methodology for measuring the prevalence of negative moods in the public. The *Sewol* disaster is an ongoing issue that requires attention and monitoring. Therefore, policymakers should recognize that the families of victims are not the only people who experience grief in the aftermath of a disaster. The public, especially neighbors who are affiliated with victims living nearby, may suffer greatly from the death of their neighbors. Ultimately, policymakers should find ways to help heal the wounds of those suffering.

APPENDIX 2:

ADDITIONAL INFORMATION AND ESTIMATES

Table 2A: Regression for Fixed-Effect Model by Period

	Y=ln(Total Spending) (1)	ln (Card) (2)	ln (Cash) (3)	ln (Spending Per Swipe) (4)
ln (Credit Limit)	0.216***	0.155***	0.123***	0.259***
	(9.98)	(7.22)	(43.73)	(27.09)
ln (Usage)	1.791***	1.808***	1.055***	0.155***
	(12.83)	(13.73)	(39.84)	(3.02)
lag_ln (Outstanding)	-0.057***	-0.053***	0.037***	-0.048***
	(-8.31)	(-8.61)	(12.79)	(-12.55)
ln (Past Due)	-0.035***	-0.016***	-0.008	-0.033***
	(-9.45)	(-4.70)	(-0.98)	(-19.70)
Bereaved_Post	**-0.029***	**-0.033****	**-0.005**	**-0.030****
	(-1.72)	**(-2.53)**	**(-0.17)**	**(-2.46)**
Neighbor_Post	**-0.013*****	**-0.016*****	**-0.027*****	**-0.011*****
	(-2.73)	**(-3.66)**	**(-2.81)**	**(-2.79)**
Distance_Post	**-0.004**	**-0.004**	**0.002**	**-0.005**
	(-0.81)	**(-1.06)**	**(0.33)**	**(-1.36)**
r2	0.507	0.540	0.085	0.020
N	10.5 mil	10.5 mil	10.5 mil	10.5 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 2B: Regression for Fixed Effect Model by Gender

	Y=ln(Total Spending)		ln (Card)	
	Male	Female	Male	Female
ln (Credit Limit)	0.227***	0.228***	0.166***	0.165***
	(11.62)	(10.54)	(8.50)	(7.67)
ln (Usage)	1.734***	1.761***	1.758***	1.781***
	(13.10)	(12.35)	(14.28)	(13.23)
lag_ln (Outstanding)	0.002	-0.014***	-0.007	-0.016***
	(0.22)	(-2.64)	(-1.19)	(-3.55)
ln (Past Due)	-0.042***	-0.032***	-0.023***	-0.016***
	(-17.96)	(-16.16)	(-8.19)	(-6.33)
Bereaved_Post	**-0.020**	**-0.060*****	**-0.038**	**-0.057*****
	(-0.72)	**(-2.64)**	**(-1.53)**	**(-3.22)**
Neighbor_Post	**-0.016****	**-0.019****	**-0.015***	**-0.028*****
	(-2.03)	**(-2.33)**	**(-1.85)**	**(-3.75)**
Distance_Post	**-0.003**	**-0.001**	**-0.002**	**-0.007**
	(-0.39)	**(-0.11)**	**(-0.30)**	**(-1.25)**
r2	0.534	0.519	0.566	0.553
N	9.1 mil	9.2 mil	9.1 mil	9.2 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

	ln (Cash)		ln (Spending Per Swipe)	
	Male	Female	Male	Female
ln (Credit Limit)	0.126***	0.171***	0.267***	0.269***
	(10.27)	(26.45)	(36.39)	(35.26)
ln (Usage)	1.455***	0.940***	0.152***	0.140**
	(32.34)	(40.17)	(2.79)	(2.48)
lag_ln (Outstanding)	0.051***	0.045***	0.015***	-0.002
	(11.75)	(9.66)	(3.93)	(-0.90)
ln (Past Due)	0.027*	-0.003	-0.040***	-0.030***
	(1.77)	(-0.38)	(-31.16)	(-27.93)
Bereaved_Post	**0.014**	**-0.044**	**-0.023**	**-0.037**
	(0.31)	**(-0.83)**	**(-1.07)**	**(-1.61)**
Neighbor_Post	**-0.043****	**-0.003**	**-0.012***	**-0.015****
	(-2.60)	**(-0.22)**	**(-1.78)**	**(-2.45)**
Distance_Post	**0.003**	**0.010**	**0.001**	**-0.011***
	(0.27)	**(0.94)**	**(0.12)**	**(-1.84)**
r2	0.115	0.070	0.027	0.018
N	9.1 mil	9.2 mil	8.6 mil	8.6 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 2C: Regression for Fixed-Effect Model by Credit Score

	Y=ln(Total Spending)		ln (Card)	
	Low25	High25	Low25	High25
ln (Credit Limit)	0.187***	0.285***	0.139***	0.185***
	(8.89)	(19.71)	(6.39)	(10.31)
ln (Usage)	1.878***	1.640***	1.891***	1.682***
	(12.20)	(13.59)	(12.90)	(15.04)
lag_ln (Outstanding)	-0.004	0.000	-0.003	-0.019***
	(-0.55)	(0.09)	(-0.48)	(-5.00)
ln (Past Due)	-0.035***	-0.040***	-0.023***	-0.012***
	(-12.55)	(-15.46)	(-6.23)	(-4.40)
Bereaved_Post	**-0.027**	**-0.023**	**-0.033**	**-0.061**
	(-0.82)	**(-0.48)**	**(-0.87)**	**(-1.49)**
Neighbor_Post	**-0.025****	**-0.002**	**-0.030*****	**-0.007**
	(-1.99)	**(-0.13)**	**(-2.72)**	**(-0.61)**
Distance_Post	**0.006**	**-0.003**	**0.002**	**-0.007**
	(0.59)	**(-0.39)**	**(0.21)**	**(-0.88)**
r2	0.594	0.459	0.607	0.517
N	4.1 mil	5.1 mil	4.1 mil	5.1 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

	ln (Cash)		ln (Spending Per Swipe)	
	Low25	High25	Low25	High25
ln (Credit Limit)	0.152***	0.135***	0.248***	0.295***
	(15.98)	(12.34)	(25.62)	(37.82)
ln (Usage)	1.232***	1.253***	0.207***	0.101**
	(80.14)	(26.71)	(2.98)	(2.30)
lag_ln (Outstanding)	0.034***	0.079***	0.007**	0.012***
	(14.56)	(13.28)	(2.24)	(4.96)
ln (Past Due)	0.039*	-0.028***	-0.041***	-0.033***
	(1.81)	(-7.54)	(-40.31)	(-19.67)
Bereaved_Post	**-0.029**	**-0.144**	**-0.008**	**-0.024**
	(-0.36)	**(-1.40)**	**(-0.25)**	**(-0.61)**
Neighbor_Post	**-0.074*****	**-0.042***	**-0.016**	**-0.006**
	(-2.91)	**(-1.68)**	**(-1.16)**	**(-0.55)**
Distance_Post	**0.021**	**0.006**	**-0.004**	**-0.011***
	(1.05)	**(0.30)**	**(-0.58)**	**(-1.75)**
r2	0.095	0.099	0.050	0.009
N	4.1 mil	5.1 mil	3.6 mil	4.9 mil
Individual	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 2D: Regression for Fixed-Effect Model by Age

	Y=ln(Total Spending)			ln (Card)		
	20s-30s	40s-50s	60s ≤	20s-30s	40s-50s	60s ≤
ln (Credit Limit)	0.230***	0.233***	0.203***	0.178***	0.164***	0.129***
	(12.14)	(10.95)	(8.90)	(9.08)	(7.96)	(6.25)
ln (Usage)	1.615***	1.795***	2.021***	1.635***	1.820***	2.034***
	(14.46)	(12.50)	(10.65)	(15.33)	(13.64)	(11.69)
lag_ln (Outstanding)	0.000	-0.002	-0.034***	-0.002	-0.010*	-0.039***
	(0.01)	(-0.33)	(-3.43)	(-0.54)	(-1.74)	(-4.53)
ln (Past Due)	-0.036***	-0.037***	-0.045***	-0.025***	-0.017***	-0.017***
	(-13.19)	(-24.87)	(-17.90)	(-8.02)	(-8.29)	(-5.82)
Bereaved_Post	**-0.023**	**-0.048****	**-0.028**	**-0.034**	**-0.047****	**-0.069**
	(-0.78)	**(-2.00)**	**(-0.62)**	**(-1.09)**	**(-2.26)**	**(-1.24)**
Neighbor_Post	**-0.026*****	**-0.006**	**-0.030**	**-0.029*****	**-0.012***	**-0.028**
	(-3.41)	**(-0.75)**	**(-1.04)**	**(-3.77)**	**(-1.71)**	**(-1.25)**
Distance_Post	**-0.004**	**-0.003**	**0.005**	**-0.007**	**-0.007**	**0.009**
	(-0.55)	**(-0.42)**	**(0.32)**	**(-0.95)**	**(-1.29)**	**(0.58)**
r2	0.534	0.522	0.544	0.563	0.559	0.572
N	6.42e+06	9.89e+06	2.18e+06	6.42e+06	9.89e+06	2.18e+06
Individual	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed

	ln (Cash)			ln (Spending Per Swipe)		
	20s-30s	40s-50s	60s ≤	20s-30s	40s-50s	60s ≤
ln (Credit Limit)	0.130***	0.158***	0.174***	0.261***	0.277***	0.239***
	(11.57)	(18.46)	(15.13)	(33.35)	(33.51)	(45.07)
ln (Usage)	1.158***	1.204***	1.014***	0.075*	0.189***	0.210***
	(58.29)	(33.07)	(24.44)	(1.72)	(3.02)	(3.41)
lag_ln (Outstanding)	0.047***	0.052***	0.037***	0.016***	0.009**	-0.026***
	(10.73)	(11.09)	(8.24)	(9.51)	(2.32)	(-3.45)
ln (Past Due)	0.015	0.011	-0.012	-0.035***	-0.035***	-0.037***
	(1.38)	(0.79)	(-1.20)	(-30.04)	(-34.01)	(-14.80)
Bereaved_Post	**-0.035**	**-0.005**	**0.016**	**-0.023**	**-0.029***	**-0.042**
	(-0.52)	**(-0.13)**	**(0.20)**	**(-1.12)**	**(-1.67)**	**(-1.01)**
Neighbor_Post	**-0.028**	**-0.016**	**-0.046**	**-0.022*****	**-0.003**	**-0.013**
	(-1.32)	**(-1.08)**	**(-1.45)**	**(-3.38)**	**(-0.46)**	**(-0.60)**
Distance_Post	**0.010**	**0.008**	**-0.000**	**-0.006**	**-0.006**	**0.004**
	(0.60)	**(0.74)**	**(-0.00)**	**(-0.79)**	**(-1.29)**	**(0.23)**
r2	0.086	0.093	0.086	0.020	0.027	0.020
N	6.42e+06	9.89e+06	2.18e+06	5.98e+06	9.23e+06	1.99e+06
Individual	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed
Time	Fixed	Fixed	Fixed	Fixed	Fixed	Fixed

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

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CHAPTER 4

INFORMATION-SECURITY BREACHES AND CREDIT-CARD SPENDING

1. Introduction

Businesses today utilize rich, abundant, available data to provide tailored services to customers. The credit-card industry's strategy in particular relies heavily on large-scale customer information. To increase opportunities for market competence and to understand customers' lifestyles, credit-card companies collect massive amounts of information and analyze customers' spending behaviors, such as the goods they purchase, the restaurants where they eat, and the places where they travel. Amid the fast-growing appetite for Big Data in the marketplace, the increased use of customer data inevitably raises concerns regarding cybersecurity and customer privacy. In the U.S., massive customer-information breaches have been uncomfortably common, and the personal information of nearly half of U.S. adults has been hacked since 2014.[10]

Although incidents of customer-data breaches are burgeoning and pose great challenges worldwide, limited research has been done on subsequent customer behaviors after a breach. Previous studies mostly focus on stock-market reactions to customer-data breaches, which generally, although not always, have temporary negative effects on companies' market values (Campbell et al., 2003). While investors often represent customers of breached companies, and investors' reactions may reflect a particular consequence of such incidents, they do not fully capture the actual

[10] http://money.cnn.com/2014/05/28/technology/security/hack-data-breach/

behaviors of affected customers. The rationale for investing in a company is not always the same as the rationale for being a customer of that company. Individuals may continue investing in a breached company even after deciding not to be customers anymore. Customers' behavioral reactions to data breaches indicate a loss of customer confidence, an intangible cost that is difficult to perceive in investors' reactions, but permanently affects firms' future cash flow. Moreover, many studies rely on survey data from small samples, which might produce biased results.

This study uses a large amount of credit-card data to investigate the effects of security failures on companies' customer bases and customers' use of compromised credit cards after information-security breaches. The event studied in this chapter is a major security breach at Korean credit-card companies in 2014. By analyzing the spending behaviors of cardholders with compromised card data, this study is intended to answer the following questions: How do information-security breaches influence individuals' likelihood of closing compromised accounts? How do information-security breaches influence the spending behaviors of cardholders who keep compromised accounts? How does past experience with compromised credit cards influence future usage of them?

The rest of this chapter is organized as follows. In the next section, I describe the security-failure incident among Korean card issuers. In the third section, I review relevant previous studies and develop research hypotheses, and in the fourth section, I present the dataset used in this chapter. The fifth section discusses the research methodology, the sixth section reports the results of the empirical analysis, and the final section presents the conclusions.

2. Information Security Breach

On January 8, 2014, Korean regulators announced that the details of 104 million credit cards in Korea had been stolen by an information-technology (IT) worker at the Korea Credit Bureau, which serves South Korea. The worker secretly copied customer information from credit cards issued by KB Financial Group, Lotte Card, and Nonghyup Financial Group onto a USB stick between October 2012 and December 2013, then sold the information to loan-marketing firms. The three credit-card issuers were unaware of the breach until the regulators publicly announced the theft. Prosecutors announced that when considering individuals who had multiple credit cards, nearly 20 million individuals were affected by the breach. The un-encrypted data included crucial customer information, including names, residential addresses, phone numbers, Social Security numbers, salaries, and credit-card details. The managers of the three credit-card issuers released public apologies and offered their resignations for their failure to prevent the massive customer-data breach. Prosecutors fined the three credit-card issuers KRW 6 million (approximately US $5,500) and banned the three card issuers from issuing credit cards to new customers for three months.[11] While credit-card companies were obliged to compensate customers for personal financial losses due to the breach, financial authorities assured that they found no evidence that the data were misused. However, angry and worried customers rushed to the companies' branches, contacted their call centers, and visited company websites to inquire whether their data had been stolen. As a result, nearly

[11] The suspension lasted from February 17, 2014 to May 16, 2014.

2.63 million customers of the three card issuers cancelled their credit cards, while 4.31 million demanded that their cards be reissued.[12] The issue of this breach resurfaced in March 2014 when financial authorities overturned their previous announcement and publicized a third-party leak. It was discovered that the personal information of millions of card holders had been sold to loan-marketing dealers.

3. Literature Review and Hypotheses

Previous studies report mixed outcomes from examining market responses to announcements of information-security breaches. Garg et al. (2003) used an event-study methodology and found an average loss of 5.6 percent in stock prices from 22 such events in 1996 and 2002. Garg et al. (2003) further investigated the heterogeneity in investors' reactions to different types of events and found that among events involving denial of services, website defacement, or theft of credit-card information, investors' reactions to the loss of credit-card information through market activity is exceptionally costly, amounting to a 15 percent drop in stock prices over the three days following events. Campbell et al. (2003), however, found limited evidence of an overall negative effect on stock value. However, they examined different types of breaches and found that the negative effects after announcements become significant when security breaches violated customer confidentiality. Campbell et al. (2003) found no significant impact when the damage was limited to technical problems. Moreover, Kannan et al. (2007) investigated whether impacts from security breaches varied by company size or time period studied. Kannan et al. (2007) found that market

[12] https://www.bloomberg.com/news/articles/2014-02-02/south-korea-to-suspend-3-credit-card-firms-over-data-theft

reactions to announcements of security breaches neither differed by firm size, nor persisted in the long term. Malhotra and Malhotra (2011) specifically looked at the effect of security breaches resulting in losses of customers' private information and found a drop of 3 percent in stock value after announcements. The loss is greater among large firms, and the gap with small firms becomes significant as the number of affected individuals increases.

Malhotra and Malhotra (2011) also noted that the loss of customer information was a type of service failure because the breached company failed to protect customers' private information. Customer service is a key determinant of customer satisfaction and market competitiveness, and severe service failures create customer dissatisfaction, provoking negative emotions and eliciting negative impressions of companies. Emotions tend to play a pivotal role in influencing individuals' decision-making and judgment, and negative emotions can result in customer "grudge-holding" behaviors against companies, such as complaining (Blodgett et al., 1995; Kim et al., 2003), disseminating negative word-of-mouth (Tsai et al., 2014), reducing interactions with companies (Bunker & Ball, 2008), and exiting the customer relationship (Haj-Salem & Chebat, 2013; Singh, 1990). Such behaviors permanently affect companies if they continue to influence customers' perception and reduce opportunities to increase customers' purchase decisions (Bansal & Voyer, 2000; Wirtz et al., 2007). Although customers expect some risks associated with service failures, and minor service failures might not provoke immediate anger or frustration (Kelley & Davis, 1994), loss of customers' private information increases their privacy concerns and perceived risk, discouraging them from continuing to do business with the companies concerned (Culnan & Armstrong, 1999; Kim et al., 2008). Therefore, I hypothesize:

H_{Ao}: The announcement of information-security breaches does not influence cardholders' use of compromised credit cards.

H_{A1}: The announcement of information-security breaches influences cardholders' use of compromised credit cards.

Previous studies emphasize the importance of switching barriers, or factors that make it difficult or costly for customers to change service providers, in determining customer retention. The underlying structures constituting switching barriers generally include interpersonal relationships, switching costs, and the availability of alternatives (Jones et al., 2000; Colgate & Lang, 2001). Interpersonal relationships refer to the bonds between customers and service providers, or the shared acknowledgement of special affiliations, whose degree determines customers' decisions to remain in the relationship, even if the service received is less than optimal (Czepiel, 1990; Gwinner et al., 1998; Molina et al., 2007). Switching costs refer to the psychological, monetary, and physical costs associated with changing service providers (Sengupta et al., 1997). In exploring the multi-dimensional characteristics of switching costs, Jones et al. (2002) classified them into three large categories: continuity, learning, and sunk costs. Continuity costs consist of lost performance costs (i.e., benefits lost due to termination of service) and uncertainty costs (i.e., perceived risks associated with new service providers). Learning costs consist of pre- and post-switching costs (i.e., searching costs and time to adjust to new service providers) and setup costs (i.e., filling out application forms). Sunk costs include a cost that has already been incurred and efforts to establish relationships with new service providers. Switching costs in general are negatively related to switching tendencies by increasing willingness to purchase services (Jones et al., 2000) and customers' dependence on providers (Morgan & Hunt, 1994), creating customer loyalty (Ping, 1993) and offsetting switching benefits (Stigler, 1961). Moreover, several studies suggest that customers continue their relationships with current service providers when they perceive no practical alternatives (Andreasen, 1985; Bendapudi & Berry, 1997; Anderson & Narus, 1990). After conducting survey questionnaires of consumers who decided to stay after seriously considering switching financial-service providers, Colgate and Lang (2001) found that inertia, or customers' lack of interest or indifference to alternatives, is the most significant factor discouraging customers from switching.

Several studies explored the role of switching barriers in the credit-card industry. Ausubel (1991) discusses the prevalence of high search costs in the credit-card industry, which can plausibly explain card issuers' tendency to preserve high credit-card rates. Ausubel (1991) suggests that credit-card rates were inflexible from 1982 through 1986 relative to market rates, with one explanation being the high search costs associated with customers searching for alternatives (i.e., money, time, and effort spent discovering better options and opening new accounts). High search costs inherently discourage consumers from switching, enabling credit-card issuers to maintain high interest rates and retain customers despite high interest rates. Calem and Mester (1995) assert that switching costs are especially high for individuals carrying large balances. Using data from the 1989 Survey of Consumer Finances, Calem and Mester (1995) found that high-balance individuals are more likely to be rejected or given less-desirable limits when applying for new credit, making switching costs comparatively high. One explanation behind this high level of rejection is that card issuers that use debt-to-income ratios to determine credit approval consider outstanding debts to be a sign of credit risk when they are unable to determine the creditworthiness of cardholders. Moreover, for cardholders whose outstanding balances are near liquidity constraints, the costs associated with closing accounts are comparatively high because it requires settling existing debts. Finally, frequent card usage is generally rewarded with various loyalty programs, such as cash back, accrual points, and upgraded services. Consumers who frequently use credit cards are more likely to feel locked in because switching requires forgoing loyalty benefits. This explanation is supported by Wirtz et al. (2007), who find that cardholders tend to increase their use of credit cards if they perceive high switching costs related to loyalty programs. Based on this research, I hypothesize the following:

H_{Bo}: Cardholders' experiences with credit cards do not influence future use of compromised credit cards.

H_{B1}: Cardholders' experiences with credit cards influence future use of compromised credit cards.

The results in this chapter show that after the announcement of information-security breaches, customers' likelihood of closing accounts increases, and that this trend continues for several months. Information-security breaches also negatively influence use of compromised credit cards by cardholders who keep their accounts, especially among those with good credit scores or who are considered to be profitable for the company. The findings in this chapter also suggest that positive experiences with credit cards are effective in retaining customers, but that the effect becomes less significant when major security breaches occur. Finally, cardholders who use credit cards as an extra source of cash show moderate reactions in their use of compromised credit cards after breaches. The findings in this study resemble Lee and Lee's (2012) findings of a negative relationship between the perceived usefulness of e-commerce websites and online customers' negative behaviors after information-security incidents, although the effect is not statistically significant in their study. The limitation of a small sample size is one potential explanation. By using a large dataset, this study provides a comprehensive understanding of customer behaviors after major information-security breaches. Moreover, by using proprietary credit-card data and an event that happened in a natural setting, this study provides empirical evidence of customers' reactions to information-security breaches. Policymakers and managers in the credit-card industry can benefit from the findings in this study.

4. Data Description

The study uses two types of datasets. The first data analyzed in this chapter were drawn from one of the compromised Korean card issuers. This proprietary data contained credit-card information from 2 million randomly selected accounts. The unit of observation is a credit-card account, and each account represented a single monthly statement for all cards held by an account owner because cardholders often possess multiple credit cards from the same issuer. The dataset consisted of cardholders with the last name Kim, which is the most common surname in Korea and is not limited to a specific birthplace, occupation, or household members. The behaviors of cardholders in the dataset, therefore, should be representative of the behaviors of cardholders in general. The names of account holders were replaced by random numbers and anonymized to protect the identities of account holders. The dataset is an unbalanced panel covering the sample period from January 2012 through May 2014, including January 2014, when the information-security breach was revealed to the public. To be included in the sample, the total credit-card balance of an account holder had to be more than zero. While the first dataset observed the behaviors of affected individuals, the second dataset provided aggregate credit-card usage. The second dataset used in this chapter consists of publicly available credit-card data provided by Financial Statistics Information System, South Korea's statistical information provider. Financial Statistics Information System provides a large range of Korean statistics, including information on credit-card usage at 20 Korean credit-card companies on a quarterly basis. I used this public dataset to investigate unique changes in credit-card usage among data-leaked companies. Similar to the first dataset, the sample period covers January 2012 through June 2014.

5. Methodology

This study presents two regression models: a logistic model and a regression model with an individual fixed effect. The former estimated customers' likelihood of closing accounts during and after the announcement of an information-security breach, while the latter estimated the ex-post spending behaviors of those who continue using credit cards. The purpose of the logistic model is to determine the effect of the information-security breach on the likelihood of exit, as well as factors influencing customers' exit decisions. The purpose of the fixed-effects regression model is to identify factors influencing the spending behaviors of customers who stay with the company after the breach.

5.1 Estimation of the Likelihood of Exit

The logistic regression model is stated in *Equation 1*:

[Equation 1]

$$Y_{it} = \alpha_i + \delta X_{it} + \boldsymbol{\gamma_1 Dec2013_{i,t}} + \boldsymbol{\gamma_2 Jan2014_{i,t}} + \boldsymbol{\gamma_3 Feb2014_{i,t}} + \boldsymbol{\gamma_4 Mar\ 2014_{i,t}} + \varepsilon_{it}$$

To estimate the effects of the information breach on exit likelihood, I used a logistic model with an individual and month-fixed effect to control for individual heterogeneity and seasonality. The dependent variable in the logistic regression is *dCancel*, a binary variable in which 1 indicates "cancelling the credit card within the next 30 days," and 0 indicates "staying with the company for the next 30 days." Occasionally, an account disappears from the dataset, not because the customer voluntarily canceled the credit card, but because the credit-card company terminated the customer's account. Involuntary account termination does not reflect willingness to exit and, therefore, might cause biased results. Most involuntary terminations occur due to inactive accounts with no outstanding balances, so I eliminated cardholders whose total balance equaled zero from the sample.

The vector of control variables, X_{it}, represents the credit-card information of individual *i* at time *t*. The control variables include *ln(Limit)*, *ln(Spending)*, *ln(PastDue)*, *Ratio_Revolving*, and *dLoan*. I listed the variable definitions and mean statistics in Table 3.1. Credit limits are based on credit scores evaluated by card issuers that use internal and external sources to examine cardholders' creditworthiness. Credit-card spending includes all credit-card transactions (e.g., card transactions through merchant accounts), cash advances, and revolving credit, but excludes card loans. Past due balances occur when cardholders do not pay previously charged debt in full by the due date. Generally, interest is charged each month on past due balances, but the past due balances in the dataset do not include interest or late fees. *Ratio_Revolving* indicates how actively cardholders use deferred-payment methods, such as revolving or installment credit. Installment credit is debt made with a specific payment plan and paid back evenly over the set period, whereas revolving credit is debt made without promising a specific payment date and whose payments can vary. In Korea, both deferred-payment methods are commonly used. *Ratio_Revolving* is calculated as the sum of deferred-payment usage divided by the total number of credit-card swipes each month. A ratio close to 1 indicates that a cardholder makes most transactions using revolving credit. While spending levels signal how actively cardholders use credit cards, balances themselves do not indicate their purposes in using credit cards. Generally, people use credit cards for transactional or borrowing purposes, and their responses to breaches can differ depending on the particular purposes for which they use credit cards. To distinguish the differences in behaviors, I added a dummy variable, *dLoan*, which equals 1 if a cardholder uses cash advances or card loans and 0 otherwise. In Table 3.1, approximately 15 percent of observations in the sample use loan services.

Table 3.1: Variable Definitions and Summary Statistics

	Mean (Std)	Variable Used	Definition
(A) Full Sample			
Credit Limit ($)	4,844 (4,327)	*ln(Limit)*	log (Credit limit+1)
Monthly Spending	584 (1,175)	*ln(Spending)*	log (Monthly credit card spending +1)
Past Due ($) >0	715 (1,638)	*ln(PastDue)*	log (Monthly past due balance +1)
Ratio_Revolving	0.37 (0.45)	*Ratio_Revolving*	Number of deferred-payment options divided by total credit-card swipes
dLoan	0.15 (0.36)	*dLoan*	equals 1 if a cardholder uses cash advances or card loans and zero otherwise
# Obs.			51,947,741
# Individuals			2,077,272
(B) Cardholders whose accounts survived as of May 2014			
Credit Limit ($)	5,053 (4,434)	*ln(Limit)*	log (Credit limit+1)
Monthly Spending	636 (1,213)	*ln(Spending)*	log (Monthly credit-card spending +1)
Past Due ($) >0	669 (1,547)	*ln(PastDue)*	log (Monthly past due balance +1)
Ratio_Revolving	0.40 (0.46)	*Ratio_Revolving*	Number of deferred-payment options used divided by total credit-card swipes equals 1 if a cardholder uses cash advances or card loans and 0 otherwise.
dLoan	0.16 (0.37)	*dLoan*	
# Obs.			45,025,055
# Individuals			1,645,651

For the purposes of this study, *exit* is defined as the disappearance of an account from the dataset as a cardholder cancels a credit card. The dataset contains information on cardholders as of the last day of each month. For an individual who reacted immediately to the announcement of the information breach on January 8, 2014, and settled a credit card during January, the final month of the account in the dataset is December 2013. Similarly, for a cardholder who postpones the exit decision until February and cancels credit cards in February 2014, the final month appearing in the dataset is January 2014. Since the focus of this study is to examine the likelihood that December 2013 is the final period, which happens when a cardholder closes his account in January 2014, the variable of interest is *Dec2013*, a dummy variable that equals 1 for December 2013 and 0 otherwise. Similarly, *Jan2014*, *Feb2014*, and *Mar2014* are dummy variables that equal 1 for January, February, and March 2014 and 0 otherwise, respectively. These variables monitor how the likelihood of exit stemming from the information-security breach announcement persists in the following months.

5.2 Estimation for Ex-Post Spending Behaviors

The fixed-effects regression model is stated in *Equation 2*:

[Equation 2]

$$Y_{it} = \alpha_i + \delta X_{it} + \boldsymbol{\gamma_1 Jan2014_{i,t}} + \boldsymbol{\gamma_2 Feb2014_{i,t}} + \boldsymbol{\gamma_3 Mar2014_{i,t}} + \boldsymbol{\gamma_4 Apr2014_{i,t}} + \varepsilon_{it}$$

To estimate whether the information-security breach influences the spending behaviors of cardholders who decide to stay with the compromised company, I used a fixed-effects regression with a standard error clustered by time. For the dependent variable, I used *ln(Spending)* and *ln(Usage)* to measure the credit behaviors of individual *i* at time *t*. *ln(Spending)* is the log of monthly spending plus 1 and includes all the transactions made through credit cards except for the card loan. *ln(Usage)* is the log of monthly credit-card usage plus 1 and measures the level of transaction frequency. The sample population used in this model is cardholders who opened accounts before the breach and held them through May 2014. Limiting the sample to surviving accounts could cause selection bias, as the cardholders in the sample might have a special reason for holding onto their accounts. The observed response then might be influenced more by this reason and less by the breach. To ensure that the results are consistent throughout the sample, I also estimated the same regression model with the full sample. Month and individual dummies were used to control for seasonality and individual heterogeneity. The vector of control variables, X_{it}, is the same as the variables used in the logistic regression in *Equation 1*.

The fixed-effects regression model estimated the spending behaviors after the breach. A motivation for this regression is to verify how spending and use of credit cards changed in a month following a major information-security breach. Therefore, the variable of interest in this model is *Jan2014*, a dummy variable that equals one for January 2014 and zero otherwise. Similarly, *Feb2014*, *Mar2014*, and *Apr2014* are dummy variables that equal 1 for February, March, and April 2014 and 0 otherwise, respectively. These variables monitor how changes in spending behaviors continue in the following months.

6. After Information-Security Breach

6.1. Stock Market and Customer Reactions

The Korea Composite Stock Price Index (KOSPI) is a representative stock market index of South Korea that lists the index of all the common stocks traded on the nation's stock market. The three compromised credit-card companies are subsidiaries of holding companies and are not publicly traded. However, the net profits of data-leaked company 1 (hereafter Data Leaked 1) exceeded 90 percent of the total net profits of its holding company; therefore, the stock price of the holding company should reflect the market response to the compromised company. Similarly, data-leaked company 2 (hereafter Data Leaked 2) is a subsidiary of its holding company, which holds a 94 percent share in Data Leaked 2. Figure 3.1 depicts the daily closing prices of KOSPI financial companies in the banking sector, Data Leaked 1, and Data Leaked 2 before and after the breach. Figure 3.1 shows a sharp fall in the stock prices for both data-leaked companies after the announcement of the information-security breach, while the stock price for the KOSPI financial company index shows an upward trend during the same period. Specifically, the average stock price of Data Leaked 1 decreased by 6.8 percent from January to February 2014, and Data Leaked 2 fell by 10 percent during the same period. On the contrary, the average stock price on the KOSPI financial company index went up by 5.2 percent from January to February 2014.

Figure 3.2 depicts the balances and growth of quarterly credit-card spending provided by the Financial Statistics Information System. This figure shows that after the information-security breach, the credit-card industry experienced an overall decrease in credit-card usage and an especially strong decrease among compromised companies. For example, credit-card balances dropped from US $19 billion to $17 billion (-10.5% growth) for Data Leaked 1, from US $14 billion to $13 billion (-7.1% growth) for Data Leaked 2, and US $10 billion to $9 billion (-10% growth) for data leaked company 3 (hereafter Data Leaked 3). The decrease in credit-card balances among the other card issuers is relatively minor, from US $106 billion to US $103 billion (-2.8% growth).

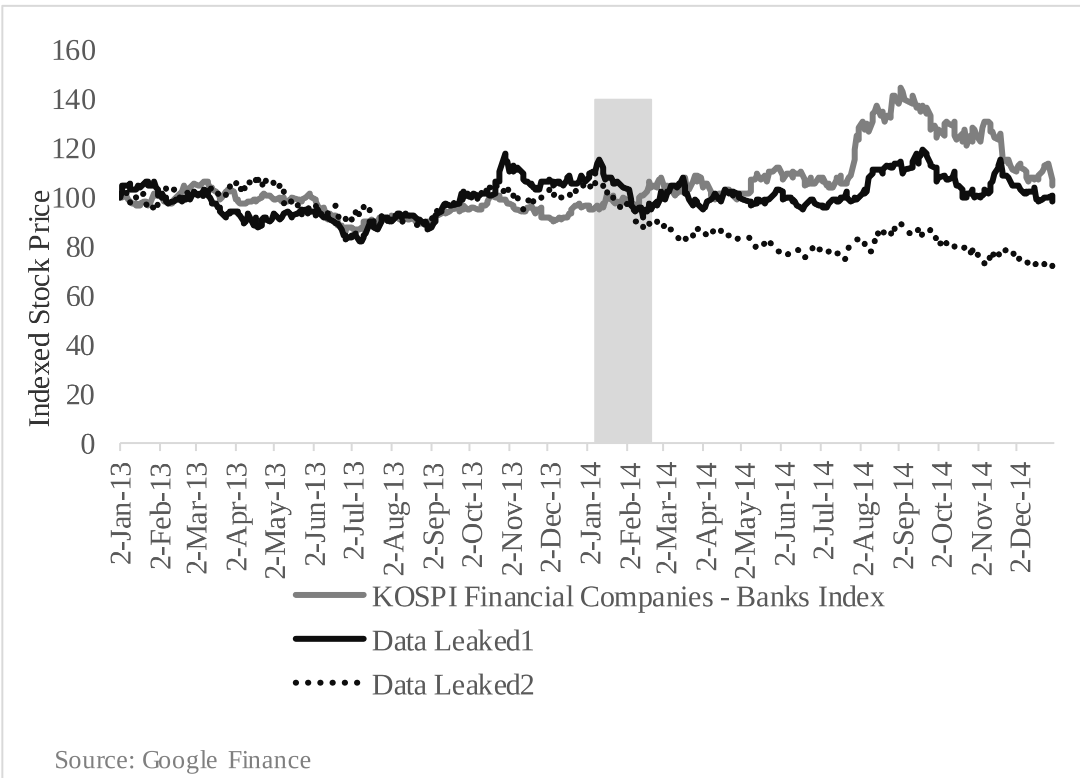

Figure 3.1: Indexed Stock Prices of Korean Credit-Card Company

Moreover, Figure 3.3 shows the number of accounts that disappeared from the proprietary dataset before and after the announcement of the information-security breach. For this graph, I used the dataset of Data Leaked 1, in which most customers' information is assumed breached. An account might disappear from the dataset not because the cardholder voluntarily closes the account, but because the card issuer terminated an inactive account. To lessen the effect of account closures by card issuers, I included only cardholders whose total balances exceeded zero in the sample. The number of closed accounts in Figure 3.3 shows that closed accounts tripled at the end of January 2014. To verify that this is not a seasonal pattern, I compared this number to the number of closed accounts in a previous year in Appendix 3 of Figure 3A, which shows that the ratio of closed accounts is moderate in all months of 2013, but exceptionally high in January and February 2014, suggesting that the information-security breach drove the higher number of closed accounts in the dataset.

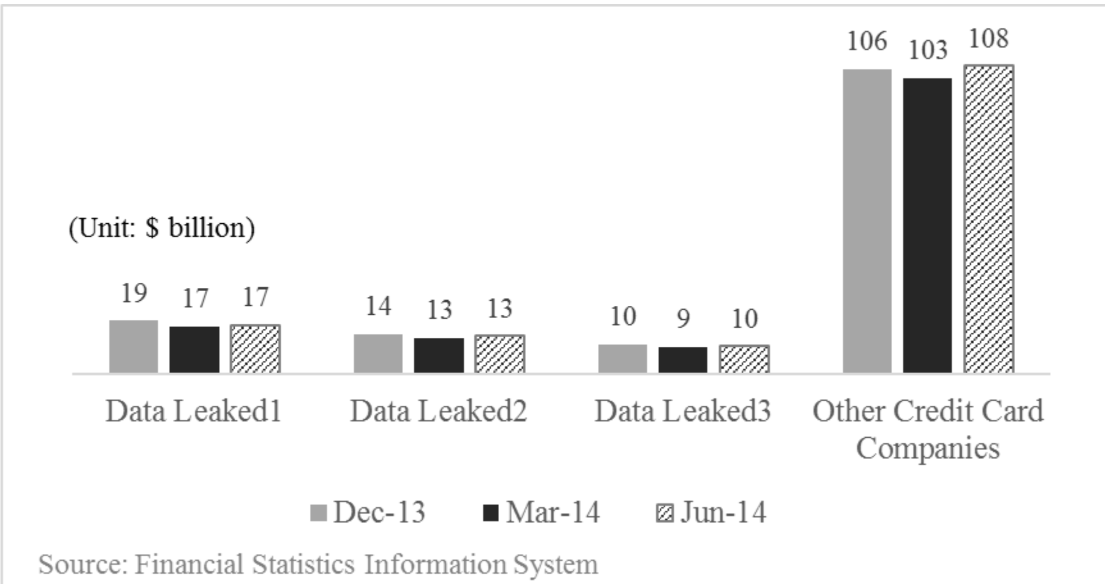

Figure 3.2: Credit Card Spending Before and After the Breach

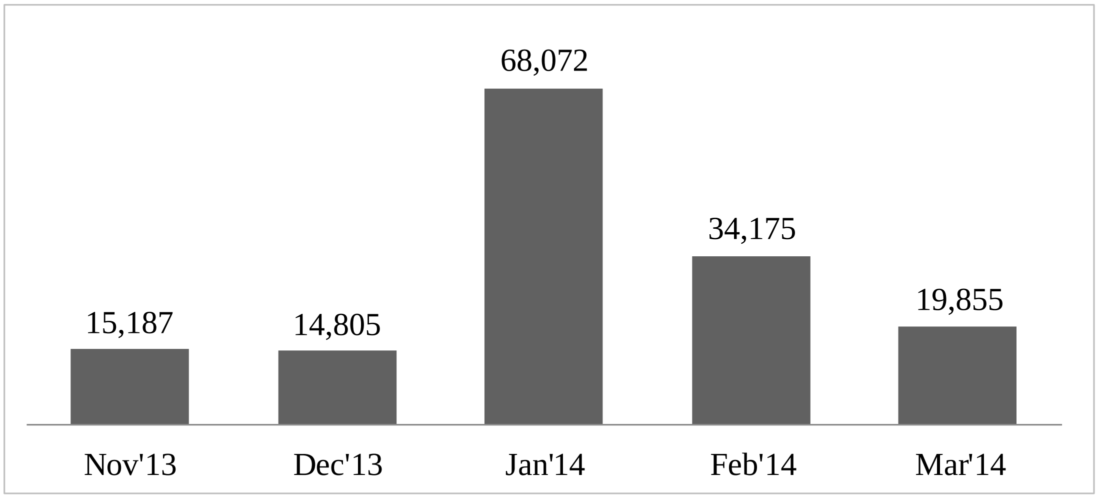

Figure 3.3: Number of Credit-Card Cancellations

6.2. Customers' Likelihood of Exit

Table 3.2 presents the results of the logistic regression in *Equation 1*, with t-statistics in parentheses. Standard errors are clustered by time. In Table 3.2, the coefficient of *ln(Limit)* is negative, which means the cardholders with high credit scores have a lower tendency to exit. Similarly, the negative coefficient of *ln(Spending)* indicates that cardholders with high credit-card balances are less likely to close accounts. This makes sense since cardholders with large credit-card balances tend to have higher switching costs than cardholders with small credit-card balances when settling credit-card debts. Moreover, using other debt options, such as deferred-payment options and card loans, is negatively related to the likelihood of exit, as indicated by the negative coefficients of *Ratio_Revolving* and *dLoan*. Although coefficients in Table 3.2 are not statistically significant at the 10 percent level, the positive coefficient of *Dec2013* suggests that the likelihood of exit increased in the month when the information-security breach was first announced, and this trend continued as indicated by the positive coefficients for *Jan2014*, *Feb2014*, and *Mar2014*.

Table 3.2: Results from the Logistic Model

	Y=dCancel
ln(Limit)	-0.867
	(-0.01)
ln(Spending)	-1.487
	(-0.38)
ln(PastDue)	-0.057
	(-0.05)
Ratio_Revolving	-0.872***
	(-2.62)
dLoan	-0.783
	(-0.40)
Dec2013	4.681
	(0.34)
Jan2014	7.286
	(1.11)
Feb2014	7.449
	(0.66)
Mar2014	7.842
	(0.65)
N	6,865,544
Month Fixed	Yes
Individual Fixed	Yes

T-statistics are reported in parentheses with a statistical significance of $p < 0.1$, $p < 0.05$ and $p < 0.01$ indicated by *, **, and ***, respectively.

In Appendix 3, Table 3A presents results of the logistic model in *Equation 1* with interaction terms. The results in Table 3A suggest that the major security failure by credit-card companies weakens the impacts of experiences with the company on customer retention. The positive coefficients of *ln(Spending)* Dec2013* and *Ratio_Revolving * Dec2013* suggest that there was a disproportionate increase in the likelihood of account closure by cardholders with large credit-card balances or who often used deferred-payment options during the first month after the breach. Moreover, the probability of exit increases substantially among cardholders with good credit scores after information-security breaches, as indicated by the positive coefficient in *ln(Limit)* Dec2013*. One possible explanation for this positive coefficient is the aggressive marketing offers by competitors attempting to attract creditworthy customers. Interestingly, some loan users' probability of closing accounts remained negative despite such events. This behavior is partly due to the relatively high switching costs for cash borrowers and the behaviors of less-creditworthy cardholders who rely on card companies as their best source of cash, which promotes the tendency to stick to current credit-card companies despite a major security failure.

6.3. Customers' use of compromised credit cards

In Table 3.3, I provide the results of the fixed-effects regression with t-statistics in parentheses. Overall, I found that the data breach had a negative impact on cardholders' use of the affected credit cards. Columns (1) and (2) in Table 3.3 exhibit results from a sub-sample dataset consisting of customers who stayed with the company, and columns (3) and (4) exhibit results from a full sample. In column (1) of Table 3.3, among individuals who maintained their accounts through May 2014, overall credit-card spending decreased during January 2014, when the breach was announced, as denoted by the statistically significant coefficient of -0.017 (t-statistics=-5.90) for *Jan2014*. The negative coefficient for *Jan2014* in column (1) implies that even if customers decided to stick with the compromised credit-card company after the breach, they reduced their use of credit cards by 1.7 percent, and this pattern continued until February 2014. Although there is a slight recovery in use of credit cards in March 2014, spending drastically declined again in April 2014, when it was confirmed that stolen data had been misused.

Table 3.3: Results from Fixed-Effects Model

	Cardholders whose Account Survived as of May 2014		***Full Sample***	
	Y=ln(Spending)	ln(Use)	ln(Spending)	ln(Use)
	(1)	(2)	(3)	(4)
ln(Limit)	0.040***	0.150***	0.037***	0.142***
	(53.53)	(113.74)	(87.81)	(53.67)
ln(PastDue)	-0.012**	-0.011**	-0.014***	-0.014**
	(-8.58)	(-9.43)	(-96.75)	(-8.80)
Ratio_Revolving	0.243***	1.037***	0.241***	1.066***
	(49.38)	(78.29)	(52.45)	(186.16)
dLoan	0.265***	0.283***	0.266***	0.297***
	(54.13)	(57.69)	(48.01)	(36.74)
Jan2014	-0.017**	-0.032	-0.021**	-0.058**
	(-5.90)	(-1.75)	(-4.98)	(-8.70)
Feb2014	-0.010**	-0.032*	-0.014**	-0.053***
	(-5.60)	(-3.31)	(-5.63)	(-26.47)
Mar2014	0.002	-0.007	-0.001	-0.021**
	(0.58)	(-1.90)	(-0.40)	(-8.17)
Apr2014	-0.019***	-0.061*	-0.020***	-0.066**
	(-15.74)	(-3.14)	(-42.31)	(-4.73)
_cons	-0.085***	0.151**	-0.076**	0.147**
	(-10.35)	(5.55)	(-8.76)	(6.41)
R-Square	.659	.75	.668	.763
N	45,025,055	45,025,055	51,947,741	51,947,741
Month Fixed	Yes	Yes	Yes	Yes
Individual Fixed	Yes	Yes	Yes	Yes

T-statistics are reported in parentheses with a statistical significance of $p < 0.1$, $p < 0.05$ and $p < 0.01$ indicated by *, **, and ***, respectively.

Column (2) in Table 3.3 shows how consumers' use of credit cards changed after the breach. Similar to the results in column (1), the frequency of using credit cards slowly decreased immediately after the announcement of the breach. In April 2014, decreases in use of credit cards became relatively severe, partly due to the third-party leak. Results from a full sample in columns (3) and (4) confirmed that the coefficients capturing the effects of the breach are consistent with the results in columns (1) and (2) in Table 3.3.

In Appendix 3, Table 3B presents results of the fixed-effects regression in *Equation 2* with interaction terms. The coefficients for the interaction variables -- including *ln(Limit)*Jan2014*, *ln(PastDue)* Jan2014*, and *Ratio_Revolving* Jan2014* -- are all negative. These results imply that the decrease was especially strong among cardholders who have good credit scores, carry past due balances, or actively use deferred-payment options. This change is especially undesirable for companies that heavily depend on profits from revolving interest and late fees because continuous decreases in the use of services may result in more severe, negative effects on management. Finally, in January 2014, when the breach was announced, it impacted loan usage as suggested by the negative coefficient of -0.004 (t-statistic=-1.42) for *dLoan*Jan2014*. However, the effect seems short-lived because loan users continued to use card loans, as indicated by the statistically significant and positive coefficient of *dLoan*Mar2014* and *dLoan*Apr2014*.

6.4. Difference in Differences

The data used in this chapter came from Data Leaked 1, where most customer information is assumed to have been breached since it was announced that nearly 20 million individuals were affected by the breach. Therefore, results in Table 3.2 and

Table 3.3 show behaviors of likely affected customers after the breach. Although a significant change in the use of credit cards among affected cardholders implies an impact from the breach, results in this chapter carry inherent challenges in identification, as behaviors of unaffected customers were not examined due to data limitations. To lessen the problem caused by identification and to strengthen the associations between the information-security breach and the changes in credit-card balances, I estimated a fixed-effects regression model in *Equation 3* using the dataset from the Financial Statistics Information System. The sample period covers January 2012 through June 2014, and there are 20 credit-card issuers owned by commercial banks, specialty banks, local banks, and credit-card companies. *Equation 3* is stated as follows:

[*Equation 3*]

$$Y_{it} = \alpha_i + \gamma_1 \boldsymbol{Qtr1\_2014}_{i,t} + \gamma_2 \boldsymbol{Qtr2\_2014}_{i,t} + \gamma_3 \boldsymbol{Qtr1\_2014}_{i,t} * \boldsymbol{dLeak}_i + \gamma_4 \boldsymbol{Qtr2\_2014}_{i,t} * \boldsymbol{dLeak}_i + \gamma_5 \boldsymbol{GDP\_Growth}_{i,t} + \varepsilon_{it}$$

A dependent variable used in *Equation 3* is *ln(Spending)*, a log of total credit-card spending, plus one. A variable *Qtr1_2014* presents a dummy variable that equals 1 if the period is in the first quarter of 2014, and zero otherwise. A variable $dLeak_i$ is a dummy variable that equals 1 for the data-leaked companies and 0 otherwise. Similarly, a variable *Qtr2_2014* presents a dummy variable that equals 1 for the second quarter of 2014, and zero otherwise. *GDP Growth* indicates a quarterly growth of Korean GDP. Company and quarter dummies are used to control for company-specific characteristics and seasonality. The year dummy is excluded in this regression because it could capture the effect of the breach. Figure 3B in Appendix 3 shows the quarterly growth of average spending. Compared with periods during the 2008 financial crisis, variations during the sample periods were relatively minor and similar to variations in non-crisis periods.

Table 3.4: Fixed-Effects Regression Using Publicly Available Data

	Period: January 2012-May 2014
	Y=ln(Spending)
Qtr1_2014	-0.025
	(-1.52)
Qtr2_2014	0.005
	(0.19)
*Qtr1_2014*dLeak*	-0.025
	(-1.10)
Qtr2_2014*dLeak	**-0.044***
	(-2.08)
GDP_Growth	0.043
	(0.98)
_cons	14.083***
	(386.81)
R-Square	.115
N	200
Number of data-leaked companies	3
Number of card issuers in the sample	20
Quarter Fixed	Yes
Company Fixed	Yes

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 3.4 displays the estimated coefficients of the fixed-effect regression. A small sample size makes several coefficients in Table 3.4 statistically less meaningful, but the coefficient in *Qtr1_2014*dLeak* and *Qtr2_2014*dLeak* suggested a decrease in the use of compromised credit cards. Specifically, the use of credit cards issued by data-leaked companies decreased by 2.5 percent, more than the rest of the companies during the first quarter of 2014. In the second quarter of 2014, when additional third-party leaks were announced, the decreased use of compromised credit cards reached 4.3 percent, as denoted by the statistically significant coefficient of -0.044 (t-statistic=-2.08) in *Qtr2_2014*dLeak*.

7. Conclusion

Today, businesses collect and use considerable amounts of customer information to establish strong bonds with current customers and attract new customers. However, the results in this study show that utilizing customer information can be a double-edged sword if companies neglect information security. This study used proprietary credit-card data to empirically investigate the impact of an information-security breach that compromised the private information of approximately 20 million cardholders. The study first examined whether the breach affected customers' exit likelihood, then explored whether the breach affected credit-card usage among individuals who remained customers of compromised companies. The findings in this study provide many useful insights. Specifically, information security breaches motivate customers' intentions to leave compromised companies, and this trend persisted for several months in this test case. The findings also confirm that previous experiences with the company have prohibitive effects on customers' exit decisions, but the impact becomes less effective at keeping customers when a major security failure happens. Moreover, although some customers remained loyal to compromised companies and decided to continue being customers, retaining accounts does not guarantee continued use of services because customers reduce use of compromised credit cards after breaches. Decreased service use is especially challenging for companies whose profits largely depend on interest fees because the number of customers who actively use deferred-payment options or carry past due balances also has decreased significantly.

The stolen data were sold to a loan company as a marketing tool to approach cash borrowers. Ironically, cardholders with loans who were supposedly the major targets of this crime were the most lenient in how they reacted to the breach. This response was partly due to high switching costs because closing accounts requires settling existing debts. The study contributes to knowledge on information-security breaches, particularly those involving loss of customer information, as well as customer reactions to major security failures. The findings in this chapter can help policymakers and risk managers in industries in which customer information plays a pivotal role in growing businesses. Due to data limitations, this research carries inherent challenges in identification because the study examined the behaviors mostly of affected cardholders. Future research can benefit from a more robust dataset. Moreover, understanding the various incentives that affect cardholders' decisions during and after security breaches could make for an intriguing follow-up study.

APPENDIX 3:

ADDITIONAL INFORMATION AND ESTIMATES

Table 3A: Results from the Logistic Model with Interactions

	Y=dCancel
ln(Limit)	-0.884
	(-0.01)
ln(Spending)	-1.817
	(-0.46)
ln(Overdue)	-0.068
	(-0.05)
Ratio_Revolving	-0.970
	(-1.45)
dLoan	-0.764
	(-0.41)
Dec2013	2.630***
	(4.15)
ln(Limit) Dec2013*	0.238
	(0.14)
ln(Spending) Dec2013*	1.388
	(0.53)
ln(Overdue) Dec2013*	0.004
	(0.00)
Ratio_Revolving Dec2013*	0.630
	(0.24)
dLoan Dec2013*	-0.008
	(-0.01)
Jan2014	4.830
	(0.23)
ln(Limit) Jan2014*	0.296
	(0.16)
ln(Spending) Jan2014*	1.392*
	(1.72)
ln(Overdue) Jan2014*	0.055
	(0.02)
Ratio_Revolving Jan2014*	0.790
	(0.29)
dLoan Jan2014*	-0.216

	(-0.06)
Feb2014	4.959
	(1.21)
ln(Limit) Feb2014*	0.308
	(0.16)
ln(Spending) Feb2014*	1.260
	(1.54)
ln(Overdue) Feb2014*	0.055
	(0.02)
Ratio_Revolving Feb2014*	0.814
	(0.31)
dLoan Feb2014*	-0.304
	(-0.07)
Mar2014	5.440
	(1.13)
ln(Limit) Mar2014*	0.299
	(0.14)
ln(Spending) Mar2014*	1.171***
	(3.47)
ln(Overdue) Mar2014*	0.067
	(0.01)
Ratio_Revolving Mar2014*	0.743
	(0.25)
dLoan Mar2014*	-0.336***
	(-4.79)
N	6,865,544
Month Fixed	Yes
Individual Fixed	Yes

T-statistics are reported in parentheses with statistical significance of $p < 0.1$, $p < 0.05$, and $p < 0.01$ indicated by *, **, and ***, respectively.

Table 3B: Results from Fixed-Effects Model with Interactions

	Cardholders whose Account Survived as of May 2014		***Full Sample***	
	Y=ln(Spending)	ln(Usage)	ln(Spending)	ln(Usage)
	(1)	(2)	(3)	(4)
ln(Limit)	0.043***	0.154***	0.039***	0.144***
	(20.03)	(25.76)	(18.64)	(25.63)
ln(PastDue)	-0.011**	-0.010**	-0.013***	-0.013**
	(-7.28)	(-4.57)	(-18.06)	(-4.82)
Ratio_Revolving	0.244***	1.034***	0.241***	1.064***
	(50.49)	(85.57)	(51.27)	(185.41)
dLoan	0.264***	0.277***	0.265***	0.292***
	(54.39)	(65.87)	(48.10)	(34.17)
Jan2014	0.040	0.048	0.027*	0.002
	(2.85)	(0.98)	(3.94)	(0.09)
ln(Limit) Jan2014*	-0.007*	-0.010	-0.006*	-0.008
	(-3.16)	(-2.14)	(-3.83)	(-2.73)
ln(PastDue) Jan2014*	-0.002*	-0.003	-0.001	-0.000
	(-3.08)	(-1.28)	(-1.12)	(-0.05)
Ratio_Revolving Jan2014*	-0.006	-0.002	-0.004	0.002
	(-2.13)	(-0.13)	(-1.43)	(0.12)
dLoan Jan2014*	-0.004	0.021	-0.003	0.025
	(-1.42)	(1.22)	(-1.17)	(1.33)
Feb2014	0.080**	0.097	0.063**	0.051
	(5.25)	(2.38)	(7.81)	(2.64)
ln(Limit) Feb2014*	-0.011**	-0.017*	-0.009**	-0.014**
	(-5.06)	(-3.55)	(-6.56)	(-4.80)
ln(PastDue) Feb2014*	-0.003**	-0.004	-0.002	-0.002
	(-4.80)	(-2.30)	(-2.01)	(-0.52)
Ratio_Revolving Feb2014*	-0.008*	0.010	-0.006	0.009
	(-2.97)	(0.75)	(-2.36)	(0.56)
dLoan Feb2014*	0.009	0.040	0.009	0.039
	(2.70)	(2.29)	(2.77)	(2.21)
Mar2014	0.060*	0.066	0.044**	0.024
	(4.21)	(1.81)	(5.97)	(1.22)
ln(Limit) Mar2014*	-0.008*	-0.012	-0.006*	-0.008
	(-3.45)	(-2.41)	(-4.22)	(-2.65)
ln(PastDue) Mar2014*	-0.005**	-0.011**	-0.004*	-0.010
	(-8.32)	(-7.51)	(-4.03)	(-2.35)
Ratio_Revolving Mar2014*	0.001	0.040*	0.003	0.036
	(0.47)	(2.97)	(0.98)	(2.61)
dLoan Mar2014*	0.019**	0.063*	0.019**	0.060*
	(5.07)	(3.29)	(5.34)	(3.25)
Apr2014	0.052	0.003	0.037*	-0.032

	(2.84)	(0.06)	(3.45)	(-0.99)
ln(Limit) Apr2014*	-0.009*	-0.011	-0.007**	-0.007
	(-4.00)	(-2.11)	(-4.98)	(-1.94)
ln(PastDue) Apr2014*	-0.005***	-0.007**	-0.004*	-0.006
	(-11.04)	(-5.38)	(-3.98)	(-1.57)
Ratio_Revolving Apr2014*	-0.004	0.037	-0.003	0.031
	(-1.65)	(2.81)	(-1.21)	(2.54)
dLoan Apr2014*	0.013*	0.058*	0.012*	0.053*
	(3.51)	(3.05)	(3.65)	(3.05)
_cons	-0.107**	0.121	-0.091**	0.130
	(-7.67)	(2.00)	(-5.70)	(2.88)
R-Square	.66	.75	.668	.763
N	45,025,055	45,025,055	51,947,741	51,947,741
Month Fixed	Yes	Yes	Yes	Yes
Individual Fixed	Yes	Yes	Yes	Yes

T-statistics are reported in parentheses with statistical significance of p < 0.1, p < 0.05, and p <0.01 indicated by *, **, and ***, respectively.

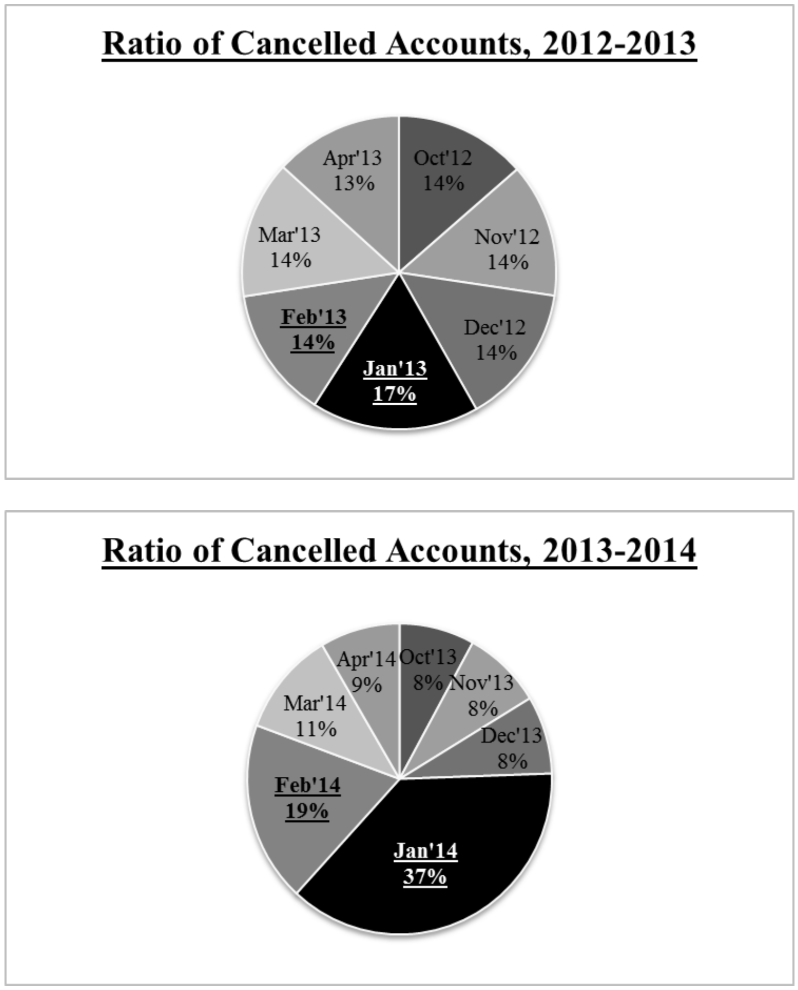

Figure 3A: Comparison of Closed Credit Card Accounts

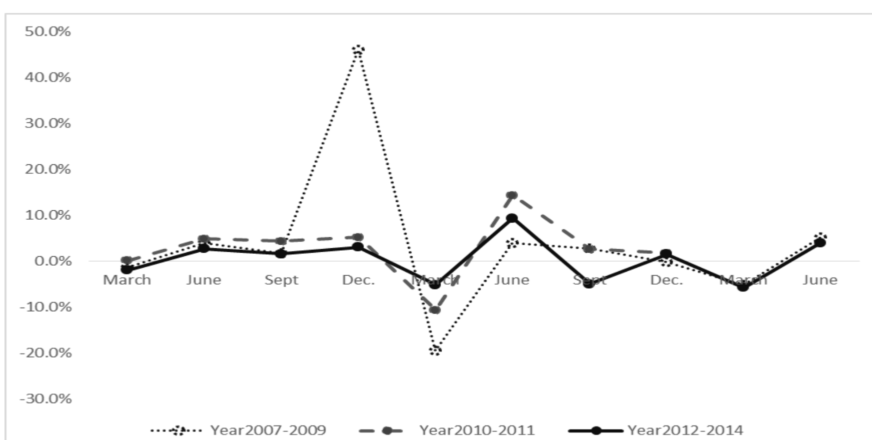

Figure 3B: Growth of Average Credit Card Spending

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CHAPTER 5
CONCLUSIONS AND FUTURE WORKS

This chapter summarizes this dissertation, discusses the main findings, comments on the limitations of the current work, and outlines directions for future work. The main focus of this dissertation is consumers' behavioral changes in response to unpredictable events. This examination of consumers' behavioral changes uses unique credit card data from a large credit card company in Korea. The events analyzed comprise government nudging policy, public grief stemming from a human-made calamity, and high-profile information security breaches. All these events—new initiatives from policymakers, tragic accidents that kill innocent people, and theft of personal information—come as unpleasant surprises but occur regularly. Despite the significance and pervasiveness of such events, little literature empirically examines their effect on consumer behavior. This dissertation is motivated by an interest in how the worst-case scenarios in daily life affect consumer behavior. In a similar vein, a deep understanding of the outcomes of environmental changes can aid preparation for future events. Thus, the main contribution of this dissertation is to offer empirical evidence on how consumer behaviors are closely tied to events in real-world settings.

Chapter 2 discusses the effect of unpaid debt reminders on credit card spending behaviors. Comparing credit card spending by cardholders who receive and do not receive unpaid debt reminders shows that informing consumers about unpaid debt balances can lead to more responsible spending. While the literature on financial knowledge and credit card borrowings focuses on the costs associated with credit card uses (Warwick & Mansfield, 2000; Lewis & Venrooij, 1995), the results in this chapter suggest the importance of recognizing one's own debt situations in credit card usage, indicating an opportunity for financial education. In addition, these findings point to the potential of nudging as an extension of policy. Although this unusually rich set of dataset on credit card usage lessens potential measurement errors, the scope of the analysis is limited to cardholders actively using credit cards. For cardholders who use credit cards occasionally, the extended intervals between purchases could reduce their ability to remember unpaid debt balances, and in this context, the effects of reminders could be counterintuitive. Future research, therefore, could extend the scope of analysis to cardholders with various backgrounds. Moreover, text alerts with other reminders, such as information on credit card interest and fees, could be tested.

Chapter 3 investigates whether emotional distress over national tragedy influences credit card usage. The national tragedy examined in this chapter is the *Sewol* disaster, which killed 261 high school students on a field trip. Most victims are from Ansan, so the cardholders are segmented by physical distance to the victims as a proxy for the level of emotional distress. The results from fixed-effects regression show that the disaster resulted in, on average, reduced credit card spending by 4 percent among those living closest to the victims' families or neighbors and by 1.6 percent among residents of the same city as the victims. These findings suggest that this disaster caused negative emotions in the public that affected credit card spending. This connection highlights the importance of understanding public sentiment during times of grief and its impact on consumer behaviors. Although this study assumes that grief is the main emotion affecting consumer behavior, the death of neighbors certainly can create many differently feelings, not only sadness. Future qualitative research could explore the different effects of emotions on consumer behavior during grief. Moreover, monitoring the persistence of these effects could help policymakers prepare for the aftermath of disasters.

Chapter 4 provides insights into customers' continued use of services when companies fail to protect customer information. In this chapter, a dataset from one data-leaked credit card company is used to estimate changes in the likelihood of canceling credit cards and spending by customers affected by a major information security breach. The findings indicate that a massive information security breach increase the likelihood of account closure and reduces the use of compromised credit cards. Moreover, the effect of past experiences with the company becomes less significant to customer retention after a major security failure.

These findings contribute to knowledge of information security breaches, which are useful for policy makers and risk managers seeking to achieve stability after data breaches. The proprietary dataset analyzed in this chapter reveals behavior mostly by affected customers, so this study has inherent identification challenges. To mitigate this problem, publicly available credit card data are used to examine whether the spending changes among the data-leaked credit card companies are unique. Although the results from fixed-effects regression suggest a disproportionate decrease in credit card use among the data-leaked companies after the breach, an explicit comparison of the behaviors of affected and unaffected consumers could better explain the impact of the beach on consumer behavior. Follow-up studies could benefit from a more robust dataset.

Consumer behaviors are determined by many movements in society, not only by factors such as prices, product attributes, and economic conditions but also by government initiatives to affect behavioral changes and sometimes by heart-breaking events. This complexity makes theoretical explanations of consumer behaviors insufficient in many cases. A careful analysis of consumer data should provide ideas about collective consciousness, unexpected trends, and social interests. Although the increasing popularity of big data drives growing interest in consumer behaviors among marketers, policy makers show little interest. Efforts to understand consumer behaviors in various dimensions and the development of privacy-protected consumer data could aid policy making more broadly.

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